MENTAL HEALTH AMONG UNIVERSITY STUDENTS IN BANGLADESH IS FORECASTED USING MACHINE LEARNING

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

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APPROVAL

This Project titled "**Mental Health Among University Students in Bangladesh is Forecasted Using Machine Learning**", submitted by Md. Sadiqul Islam Shawn 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 25th January 2024.

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I hereby declare that, this project has been done by us under the supervision of **Dr. Touhid Bhuiyan, Professor, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Medical professionals diagnose depression based on patient self-reporting and mental status questionnaires. Mentally ill people are reluctant to seek mental health treatment, in addition to the fact that the approaches vary greatly depending on the patient's state of mind at the time. Academic fields typically offer their students bright futures. But among the many other things that could cause a student to experience depression are peer pressure, academic competition, loneliness, and many other things. This study aims to identify depression in college students using a big data analytics template. It is asserted once more that the framework models the relationship between depression and factors like isolation and separation, which are thought to have the most profound effect on students. In summary, the journal assesses how well the suggested framework performs using a sizable real dataset gathered from various Bangladeshi university students, and it demonstrates that machine learning models detect depression in universities more accurately than traditional methods. I will apply six pre-trained models (Logistic Regression, Decision Tree, Random Forest, Gradient Boost, KNN, and Naive Bayes) to classify and identify this issue. Among them, Logistic Regressiongave performed better than any other proposed model. In comparison to other models, the model provided good detection accuracy.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Depression is a dangerous condition that impairs your capacity for daily activities. You could not feel like yourself and spend most of your time in sadness or anxiety. Depression can linger for months or years, and it can be minor or severe.

Depression is a medical illness with a wide range of underlying causes. It frequently develops in persons with various health issues and might happen for no apparent reason.

Pregnant women are more likely than males to experience depression; among women, one in ten report having depression at some point in their lives. Additionally, older adults—especially those over 65—frequently suffer from depression. Depression is becoming more widespread among college students in the twenty-first century for a variety of reasons.

Your ideas, feelings, and behaviours are all impacted by depression. It might also impact your interpersonal interactions, particularly with close friends and family. Your symptoms make it difficult for you to operate regularly at home or work, which could lead to major issues with your social life and productivity. Depression can make it difficult to carry out regular tasks like getting ready for work or meeting friends for lunch on the weekends.

1.2 Motivation

In the past, depression and other mental health conditions were heavily stigmatized. Many people were scared to get help because they believed it would make them appear mentally or physically frail. Even now, there is still a stigma associated with depression, particularly among people who experience it. This research paper's goal is to show how raising awareness about depression might help lessen the stigma associated with it. It is believed that by comprehending the origins and consequences of depression, I may be able to motivate more individuals to seek treatment when they are suffering.

1.3 Rationale of the Study

The study's justification stems from the urgent social issue that mental health is becoming increasingly prevalent, especially among college students. Given the startling frequency of depression as a significant barrier to both personal and academic success, a thorough investigation is imperative. By focusing on the intricate dynamics of depression identification, customized intervention tactics, and the provision of support systems specifically suited to the difficulties experienced by university students, my research aims to contribute significantly to the larger conversation on mental health.

The need to close current knowledge gaps and the unique socio-environmental elements influencing mental health in the academic context further support the reasoning. Fostering a healthier, more supportive learning environment will require a deeper understanding of depression, its antecedents, and effective intervention options as the expectations and pressures on students continue to change.

1.4 Research Questions

My study project is structured by a series of probing questions intended to reveal the intricacies of depression among college students. These queries act as lightbulbs, shedding light on particular aspects of my investigation and directing its course:

- What are the main causes of the increase in depression among college students?
- How can socioenvironmental dynamics affect students' mental health in university?
- What part do social expectations and the demands of the classroom play in depression symptoms?
- Do the frequency and experiences of depression among students exhibit any clear gender-based patterns?
- How much do peer- and institutional-based support systems lessen the effects of depression?

1.5 Expected Outcome

The expected outcome of this research is to contribute valuable insights and tools for addressing depression among university students in Bangladesh. Specifically, the research aims to achieve the following outcomes:

- Offer suggestions for enhancing the student welfare program in Bangladeshi universities.
- Create a machine learning model with depression detection capabilities.
- Increase attention to university students' mental health.
- Examine trends in several variables that are likely to cause depression in college students.

These outcomes are intended to guide and inform strategies for improving mental health support systems, fostering awareness, and implementing preventive measures in Bangladesh's university education context.

1.6 Project Management and Finance

My method has demonstrated effectiveness and financial responsibility in project management and finance. Notably, this research has had very little financial impact because it has made creative use of the platforms and tools that are readily available. The cash expenditure has been deliberately reduced by utilizing open-source software, gaining access to survey datasets, and utilizing computational resources within my academic domain.

The study has used tools aligned with open science ideals and tapped into free repositories to navigate the digital terrain skillfully. This prudent use of resources demonstrates my dedication to thrift and guarantees the long-term viability of the research process.

My research management model promotes accessibility by adopting a lean finance strategy, which allows the research outputs to be widely disseminated without imposing financial obstacles. This cost-effective strategy fits the goals of democratizing knowledge and encouraging a cooperative research atmosphere.

1.7 Report Layout

The report is divided into six chapters, each of which has been painstakingly written to add a distinct viewpoint to my main research story.

- Chapter 1: Introduction
- Chapter 2: Background
- Chapter 3: Research Methodology
- Chapter 4: Experiments and Discussion
- Chapter 5: Impact on Society, Environment, and Sustainability
- Chapter 6: Summary, Conclusion, and Implication for Future Research
- Reference
- Plagiarism Report

CHAPTER 2

BACKGROUND

2.1 Preliminaries/Terminologies

Machine learning, a subfield of artificial intelligence and a marvel of computer science is one of the most effective tools I currently have to combat depression. Machine learning excels in handling intricate datasets and determining how to model these islands. In machine learning, I begin with a predetermined objective. I feed the computer every piece of information it can obtain. Once a machine combines all the data, it tries to learn as much as possible.

Simultaneously, a model that incorporates all of these variables will discover how that specific aim is responded to by someone or something. In addition, several methods have been used to identify depression. Some machine learning techniques on multiple datasets are evident from them.

2.2 Related Work

Helbich et al. used the Patient Health Questionnaire (PHQ-9) depression module to estimate the severity of depression[9]. By taking into account certain characteristics, such as the social and physical neighborhood environments, they were able to increase the classifier's accuracy. Furthermore, a random forest classifier, gradient boosting machine, and artificial neural network were utilized to determine the severity of depression and to provide the desired PHQ-9 score. The PHQ9 scores were produced in the models, considering several variables, including age, gender, marital status, work status, and a few others. The findings indicated that each person's level of depression increased with their PHQ-9 scores. Conversely, a lower PHQ-9 suggested a happier person. The study also revealed that those working and those earning more money or education had considerably lower PHQ-9 scores than those in worse financial situations. The authors determined that, in contrast to the physical environment, the most significant determinants were the social environment and individual characteristics.

Similar research was done by Kumar and Chong [6] in their paper "Correlation Analysis to Identify the Effective Data in Machine Learning: Prediction of Depressive Disorder and Emotion States," which considers the data set's physiological and meteorological characteristics. Temperature, Atmospheric, Season, and Atmospheric were determined to be the four most significant weather characteristics after feature selection. Furthermore, Tana et al. used infodemiology to conduct a statistical analysis of the prevalence of depression [17]. The yearly, seasonal, and daily prevalence of phrases and keywords connected to depression on Twitter was plotted. It was shown that tweets about depression peaked throughout the winter months.

Shahriar et al. attempted to identify clinical depression in a different study by applying machine learning algorithms and considering a few common characteristics [10]. Shahriar discovered that K-means clustering produced the lowest results, 68.15%, while random forest produced the best accuracy, 83.80%. However, based on the algorithms' accuracy, he produced another intermediate dataset after the models were used on a primary dataset. The machine learning methods, performance metrics, and precision improvement were encouraging in this instance. For example, KNN classifiers saw an increase in accuracy from 83.52% to 93%, and so on. With the updated data, he could perform statistical analysis on various variables, including assets, gender, marital status, education level, etc. In summary, Shahriar attempted to infer clinical depression from the socioeconomic attribute analysis.

In addition to socioeconomic variables, there was a little decline in mental health among individuals under lockdown due to the recently widespread COVID-19 virus. Zhang and Ma [12] conducted a study before the country-wide lockdown triggered by the COVID-19 pandemic in Liaoning Province, China. They found the pandemic was linked to a mildly stressful effect in their sample.

Hosseinifard et al.'s classification of depressed patients and healthy individuals was based on the use of machine learning algorithms and nonlinear features extracted from EEG data [1]. Two classes of individuals were selected among the interested volunteers for the research project: forty-five were depressed subjects, and the other forty-five were normal subjects. The discovered categories were divided using logistic regression, linear discriminant analysis, and K-nearest neighbor. It's interesting to note that merging all other nonlinear characteristics and reusing them in classifiers increased the accuracy of logistic regression from 83.3% to 90%. However, several non-additional characteristics were also required to understand the EEG signal of sad participants properly. EEG signals differ greatly between a normal person and someone with mental illness; depressed individuals might be identified with high accuracy. To reiterate, depression causes EEG signals to be produced in several brain regions. Therefore, it would only take a little while to cure depression by looking into those specific brain regions. In conclusion, this work may be a valuable resource for the nonlinear analysis of EEG signals that detect depression.

Razavi et al. [11] used continuous cell phone patterns to identify sadness. Additionally, they increased the classifier's accuracy by accounting for a few explicit variables, such as gender and age. Consequently, the scientists suggest tracking continuing therapies using cellphone data, mental health applications, and user internet history. When compared to various machine learning algorithms, they discovered that a random forest classifier produced the highest accuracy of 81% in identifying sadness.

Even though Bangladeshi university students are my target audience, research on other populations will improve my comprehension. Sau and Bhakta's [5] research looked at identifying anxiety and depression in older adults. This was one of the studies that used a sizable quantity of data. Large data sets also made it possible to train the data set using a variety of machine-learning algorithms. The Random Forest method outperformed the others, as it did in most cases.

Haque [14] et al. carried out their study on predicting mental health conditions of children between the ages of 4 and 17 in binary format (depressed or not depressed), which was similar to the earlier work by Sau and Bhakta. It is rare to have a conversation about mental health issues. The data set needed to be more balanced despite the sample size being similarly large. As a result, AUC and ROC(AUC) scores were also measured, proving that accuracy could have been a more reliable way to gauge performance. Here, too, the Random Forest algorithm performed well. Three main datasets (Cohn-Kanade, RU-FACS, and McMaster Pain Archive) were utilized by Jeni et al. [2] to study how imbalanced data sets affect machine learning models. It was discovered that all performance measurements were weakened by uneven distribution, except the area under the ROC curve.

The aim of the study "Self-Reliance and Relations with Parents as Predictors of Anxiety and Depression in College Students" by Schwanz et al. [4] was to use these factors to predict anxiety and depression in college students. 153 pupils took part. On the BASC, the HDI, the STAI, the trait anxiety, and the self-reliance tests, each of the 153 participants scored T for self-reliance, T for parent relations, and T for depression. Measures' correlation matrix and descriptive statistics. Using the Behavior Assessment System for Children, Second Edition Self Report of Personality College form, participants' self-reported judgments of their connections with their parents and their degree of self-reliance were measured (BASC-2 SRP-COL).

The Hamilton Depression Inventory (HDI) is a measure designed to identify and evaluate specific symptoms of Major Depression as described by the DSM-IV. There are 23 items on the entire form. STAI was also employed. Multiple regression analyses revealed that self-reliance scores were significantly more predictive of anxiety and depression than parent relationships in the prediction of each of the outcome variables. Analogously to this study, Rois et al. [13] conducted a predictive analysis study to estimate the prevalence and predictors of perceived stress among Bangladeshi university students. Pulse rate, SBP, DBP, sleep status, smoking, and background [department] were the six predominant factors. Random Forest was the most effective training algorithm out of all of them. Although the survey only included a small number of items, Choudhury et al.'s other paper [8] focuses on predicting depression among Bangladeshi students.

Finding useful data for correlation analysis is approached quite differently in a publication by Kumar and Chong [7]. The whole-brain functional connectivity was analyzed in the article to identify depression. To solve the issue, support vector classification was applied. Additionally, a dataset was generated by examining several brain regions in volunteers, including the cerebellum, emotional network, visual cortical areas, and so forth. In this instance, SVM accurately identified depression with a 94.3% prediction rate. Once more, stating that out of all the publications on this topic, their report produced the highest accuracy. Furthermore, in this instance, the probability of the accuracy being incorrect was just · 0.0001. Additionally, information from the functional six regions was required for the study. Once again, asserting that, in this instance, the accuracy provided by the supporting vector machine was 92.5%.

By using a multinomial logistic regression model that uses variables that are highly correlated with the outcome but have low inter-correlation as predictors, Jin et al.'s paper, "Developing Depression Symptoms Prediction Models to Improve Depression Care"[3] significantly improved the rate of true positive for predicting major/severe depression.

Even though a lot of research has been done on the relationship between stress and depression, there is still a lot more to learn about how to identify depression in individuals. One such study that identifies depressive symptoms and self-esteem levels was conducted by Taawab et al. [16]. This results from various parenting philosophies that employ supervised learning methods. A dataset that the researchers had developed was derived from roughly 500 survey replies. In addition to utilizing a variety of Python libraries, supervised models like Bi-Directional LSTM, Gradient Boost Classifier, and Logistic Regression provide superior accuracy compared to alternative methods. The Gradient Boosting Classifier (GBC) performed the best, with an accuracy of 95% and an F1 score of 83.28% using 80% training data and 20% testing data. Moreover, word embedding methods produced a performance with 83.21% accuracy and 83.50% recall score in effectively identifying youngsters with depression and issues with self-esteem.

In a similar vein, raise et al.'s study from 2015 [15] focused on early postpartum depression detection in Bangladesh, an area with scant research. This study gauges Bangladeshi moms' levels of postpartum depression. Low: 0–7, Medium: 8–15, High: 16–23. 150 moms participated in a poll that produced the data set. Utilizing the Synthetic Minority Oversampling Technique (SMOTE), the data imbalance was rectified. Several machine learning models were used to test the data set, and different performance indicators were used to gauge each model's effectiveness. The best results were obtained from a random forest.

I will use a different strategy than this research. I aim to create several machine-learning models that can identify sadness in college students by utilizing socioeconomic data. We'll also produce another instant dataset to improve the models' performance.

2.3 Comparative Analysis and Summary

The core of my research is a thorough evaluation and synthesis of the body of knowledge regarding methods and literature relevant to mental health detection. I aim to highlight each strategy's subtle differences and similarities by contrasting different strategies. This comparative analysis offers a broad perspective, clarifying the changing field of research on mental health detection.

The research compared different models for mental health detection and concentrated on essential algorithms such as Random Forest, Decision Tree, Gradient Boost, KNN, and Naive Bayes. The interpretability of Decision Trees and the ensemble method of Random Forest proved effective. At the same time, the high accuracy was attributed to the iterative refining of Gradient Boost and the local pattern capture of KNN. Naive Bayes showed effectiveness by utilising probabilistic classification. Together, the findings demonstrated how well these models could handle the complexity of mental health data and offered insightful information for the study design. Table 2.1 shows the comparison between the existing & my study.

Table 2.1: Comparison Between Existing & My Study

Key of Comparison	Existing Study	My Study
Purpose of study	Most published publications investigate and evaluate different approaches to mental health screening.	The research attempts to create and assess machine learning models for mental health detection to advance the discipline. The study compares several algorithms to improve our knowledge of tactics that work, which may have ramifications for the welfare of the individual and the larger society.
Dataset	Most data are pre-collected	All 943 data were collected using Google Forms.

2.4 Scope of the Problem

Getting right to the point, this part describes the extent of the issue my study attempts to solve. I lay down a framework for comprehending the complexities of mental health detection by describing its parameters and dimensions. Additionally, I elaborate on the contextual elements that impact mental health problems' appearance, illuminating the problem's complex character. This distinction highlights the applicability and importance of my work and is essential for placing my research in the larger framework of mental health studies.

2.5 Challenges

Throughout the research process, various challenges were encountered and addressed. Some challenges include:

- **Data Collection:** Gathering comprehensive and accurate data from university students can be challenging due to privacy concerns, reluctance to disclose mental health issues, and the need for a diverse and representative sample.

- **Stigma:** Addressing the stigma associated with mental health conditions, particularly depression, poses a challenge. Overcoming societal attitudes and fostering an environment where individuals feel comfortable seeking help is essential.

- **Model Generalization:** A critical challenge is ensuring that the machine learning model developed is applicable and effective for a broader range of university students beyond the dataset used for training.

- **Interdisciplinary Approach:** Effectively addressing mental health issues requires collaboration between various disciplines, including psychology, medicine, education, and technology. Integrating insights from different fields can be challenging but is crucial for a comprehensive understanding.

CHAPTER 3

METHODOLOGY

3.1 Research Subject and Instrumentation

My research aims to enhance student welfare and create a model for identifying depression by exploring the factors behind its cause. In Bangladesh, depression is a significant problem worsened by social stigma and a lack of awareness, especially among university students. I clarify my study's main points, outline the study's topic, and describe the analytical instruments I used. I go into great detail about the specifics of my research topic, including the components of mental health that I want to investigate and comprehend. Concurrently, I discuss the tools I used, including the technologies and techniques I used to gather and examine data. This offers insight into the tools I have selected, intending to strengthen the basis of my study to conduct a thorough and knowledgeable investigation of the topic.

3.2 Data Collection Procedure/Dataset Utilized

The two primary purposes of datasets in machine learning are to train models and to serve as a standard to gauge the performance of the models that have been trained. Creating the dataset for my predictive analysis model took a lot of work. I decided to build my dataset by using a Google Form to poll students from different colleges to examine the trends and patterns in the mental health of today's students. While maintaining the participant's privacy and comfort, I also needed to gather as much pertinent information as possible. As a result, I made the form anonymous and asked each participant 26 questions. There were 943 answers in all.

Table 3.1: Queries of my survey, grouped by data types

Binary	Multiclass	Numeric
Gender	University year	Age
Born in capital	Educational background	Number of family members
Earning as of now	Relationship status	Number of children
Satisfied with academy	Monthly income	Sleeping hours
Any physical disabilities	Monthly living expense	
Ever been in a road accident	Social gatherings a week	
Any childhood trauma	Time on social media	

Taking any medication	Social life satisfaction	
Religious person		
Any indoor/fun activity		
Sports/gym		
Coffee person		
Any addictive substance		

3.2.1 Data Pre-processing

The dataset's entries are all string types, as is customary. The final question, out of the 26 (each corresponding to a column), asks whether or not the student is experiencing depression. Since the model will conduct binary classification on the dataset, this query is regarded as the target class for my dataset and is a binary class categorical query. Of the twenty-five queries (features of the dataset) left, four were numerical options, eight were multi-class categorical, and thirteen were binary-class categorical. The data type of each feature is shown in the table below. The original feature names, which were the form's questions, were altered to more suitable feature names that resembled variables before data preprocessing. Additionally, I looked through the data set for any missing values and discovered that the no_of_children(80), any_physical_disabilities(1), and ever_in_a_road_accident(1)—had a total of 82 missing entries. I used the feature's mode to impute missing values.

The binary categorical features were of the agree/disagree kind, with two possible answers: yes and no. I used the panda package's replace method to substitute the values with 0 and 1.

Every numerical value had a finite range and was a discrete integer. The sleeping duration feature and the age feature values were condensed into smaller groupings. As there was no particular order of relevance in the values, these two features, together with the remaining integer-valued features (number of family members and number of children) and the university year column (multiclass feature), were then one-hot encoded.

Since the values of the remaining seven multi-class categorical features were ranked, they were label encoded last.

	Timestamp	1. What is your Gender?	2. What is your age?	3. Which year of university are you in?	4. How many members are there in your family?	5. Which educational background are you from?	6. What is your relationship status?	7. If you have any children, how many do you have?	8. Were you brought up in the capital city of Bangladesh?	9. Do you have any part time job or income source?	...	17. Do you consider yourself as a religious person?	18. How often do you find yourself going out to social gatherings every Week?	19. Are you a regular participant in novels/movies/series/Ludo/chess or any indoor fun activity?	20. Do do sp or regula
0	2/16/2023 12:58:58	Male	24	4th	4	English Medium	Single	0	Yes	No	...	Yes	Weekends only	No	
1	2/16/2023 16:08:33	Male	25	Post-graduation	6	Bangla Medium	Single	0	No	Yes	...	Yes	I rarely go to social gatherings	Yes	
2	2/20/2023 17:36:59	Male	24	4th	4	English Medium	Single	0	Yes	Yes	...	Yes	I go out on weekends and also weekdays	No	
3	2/20/2023 18:17:38	Female	21	1st	4	Bangla Medium	Single	0	No	No	...	Yes	I rarely go to social gatherings	No	
4	2/20/2023 18:24:50	Male	23	3rd	4	Bangla Medium	Single	3	Yes	No	...	Yes	I go out on weekends and also weekdays	Yes	

5 rows × 27 columns

Figure 3.1: Dataset before pre-processing.

```
data.head()
```

	gender	born_in_capital	income_source	is_satisfied_with_academic_performance	any_physical_disabilities	ever_in_a_road_accident	has_any_childhood_trauma	is_taking_medication	is_a_religious_pe
0	0	1	0	0	1	1	1	1	
1	0	0	1	1	0	1	0	1	
2	0	1	1	0	0	0	0	0	
3	1	0	0	0	0	1	1	0	
4	0	1	0	1	0	1	1	0	

5 rows × 44 columns

Figure 3.2: Dataset after pre-processing.

My dataset is significantly altered after completing all the preprocessing procedures, and each now contains discrete integer or binary values. Now that the dataset has been converted, feature scaling and model implementation are possible.

3.2.2 Test Data, and Train Data

In an experimental setup, allocating 70% of the data for training and 30% for testing is a thoughtful approach to achieve a balance between model learning and evaluation. This method is crucial for evaluating the model's capacity for handling unknown data and generalization performance, both of which improve the validity of your research findings.

3.2.3 Feature Scaling

Feature scaling standardizes or normalizes features, reducing them to a smaller scale or range. The primary objective of feature scaling is to bring all features to a uniform scale without altering the relative differences among their values. While feature scaling is generally unnecessary for tree-based and decision-based algorithms, it proves particularly beneficial for algorithms like Logistic Regression and K-Nearest Neighbors.

Standardization, also recognized as Z-score normalization, adjusts features to possess a "mean (average) of 0" and a "standard deviation of 1". A "mean of 0" signifies that the average of all values within a feature is precisely 0 or very close to 0. On the other hand, a "standard deviation of 1" indicates that the spread of values in the standardized dataset resembles what is expected from a standard normal distribution—a bell-shaped curve with a mean of 0 and a standard deviation of 1. Standardization ensures that values are scaled to maintain a consistent spread, resulting in a standard deviation of 1.

3.3 Confusion Matrix

The cornerstone of performance evaluation, a confusion matrix provides a comprehensive view of a machine learning model's effectiveness using test output data. It calculates four essential terms: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which will be briefly elucidated in the subsequent analysis.

Table 3.2: Confusion matrix format

	[Predicted negative]	**[Predicted negative]**
[Actual negative]	True Negative - Predicted false, actual was false	False Positive - Predicted true, actual was false
[Actual positive]	False Negative - Predicted false, actual was true	True Positive- Predicted true, actual was true

I performed feature scaling in training and testing set via StandardScaler class imported from sklearn.preprocessing package. The formula for standardization is where x(stand) is the standardized value of the feature. x is the original value of the feature. Mean(x) is the mean (average) of the feature (calculated by the StandardScaler). Standard deviation (x) is the standard deviation of the feature (calculated by the StandardScaler).

$$x(stand) = \frac{Mean(x)x}{StandardDeviation(x)}$$

3.4 Statistical Analysis

I analyse the statistical analysis used to assess the effectiveness of the mental health detection model. A close examination is conducted on critical performance evaluation criteria like accuracy, precision, recall, and F1 score. The importance of each metric in determining the model's efficacy is thoroughly examined in this section. Furthermore, I go over confusion matrices as an effective method for visualizing the model's performance and understanding how well it can identify markers of mental health. The meticulous analysis of these statistical features facilitates an in-depth comprehension of the model's potential and constraints.

3.4.1 Performance Evaluation Metrix

The classification report is a crucial metric for assessing model performance in machine learning. Unlike relying solely on accuracy scores to determine the optimal model for a given dataset, the classification report delves into various factors contributing to performance evaluation. The report includes the following key elements:

3.4.3 Accuracy

Accuracy gauges the proportion of correctly predicted samples from the overall dataset. The accuracy formula follows:

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

3.4.4 Precision

Precision signifies the ratio of True Positive results to all Positive predictions, often called positive predictive value. The precision formula is given by

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

3.4.5 Recall

Also known as sensitivity or true positive rate, recall is the ratio between the number of accurate predictions and true positive results. The recall formula is expressed as

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

3.4.6 F1 Score

The F1 score, often called the harmonic mean of recall and precision, is computed as

$$F1\ Score = \frac{2*TP}{2*TP+FP+FN}$$

These metrics collectively evaluate a classification algorithm's predictive efficiency, enabling a more nuanced assessment beyond simple accuracy measurements.

3.5 Proposed Methodology/Applied Mechanism

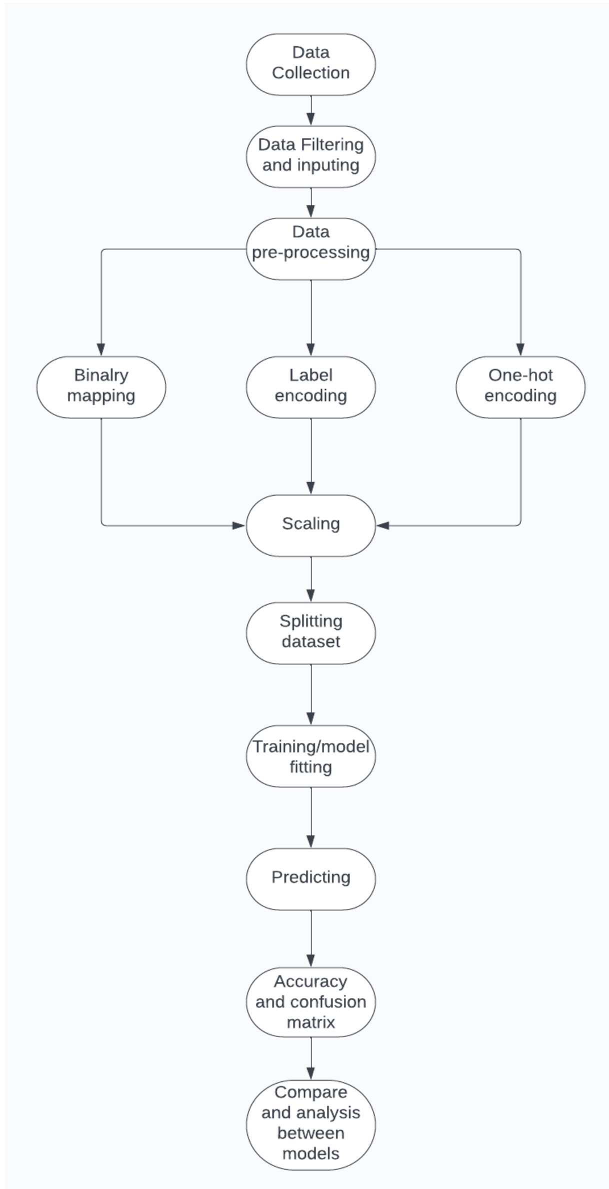

Figure 3.3: Flowchart of Methodology.

From my literature examination, I have deduced that certain classification algorithms exhibit notably higher accuracy than others. These algorithms include:

- Logistic Regression,
- Decision tree,
- Random Forest,
- Gradient Boost,
- KNN,
- Naive Bayes.

My research paper will involve implementing all of these algorithms, and their performances will be evaluated using various metrics such as accuracy score and confusion matrix. The accuracy score is a fundamental yet crucial concept in assessing the effectiveness of any machine learning model. It is the ratio of correct predictions to the total number of samples.

A detailed analysis of the performance of the aforementioned six algorithms will be conducted in the subsequent sections of my research paper.

3.5.1 Logistic Regression (LR)

I utilized the Logistic Regression model imported from the sklearn.linear_model module. The dataset was partitioned into training and testing sets at a ratio of 4:1. Subsequently, the model was trained on the designated training set, and the predicted values were stored. The model demonstrated an accuracy of 97.88%. The corresponding confusion matrix for Logistic Regression is presented in Fig 3.4.

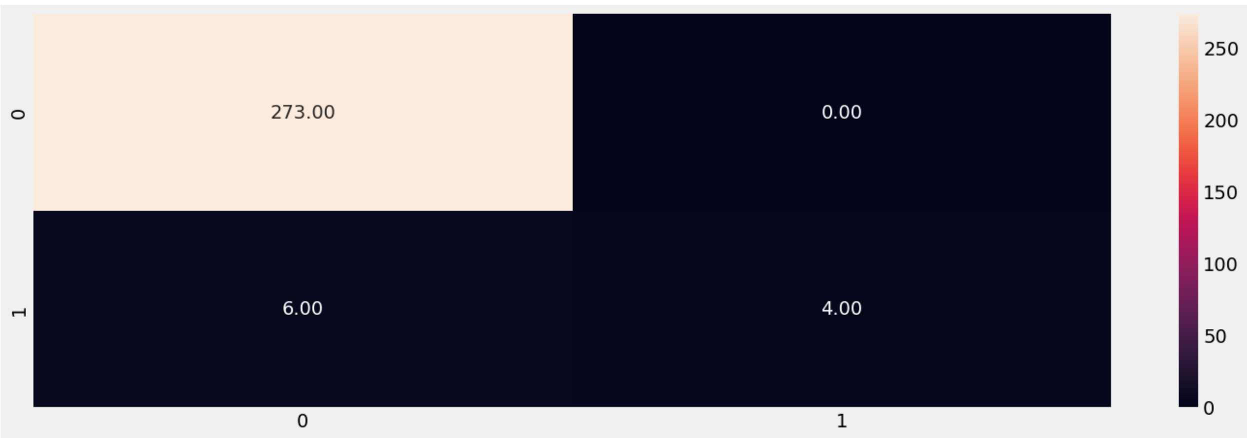

Figure 3.4: Confusion matrix for LR.

3.5.2 Decision Tree (DT)

Following a similar procedure to the previous model implementation, I employed the DecisionTreeClassifier from the sklearn.tree package. The accuracy achieved was 97.35%, and the resulting confusion matrix is depicted in Fig 3.5.

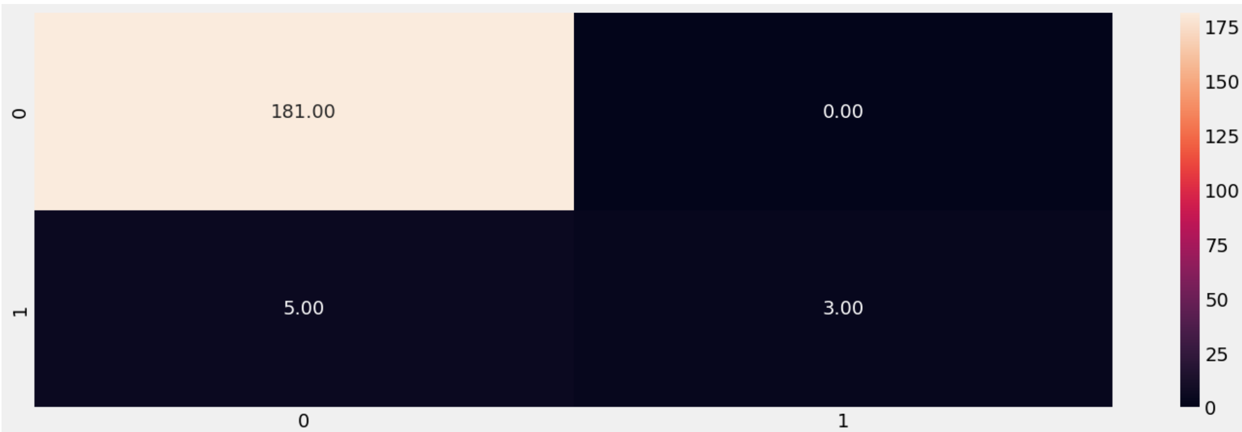

Figure 3.5: Confusion matrix for DT.

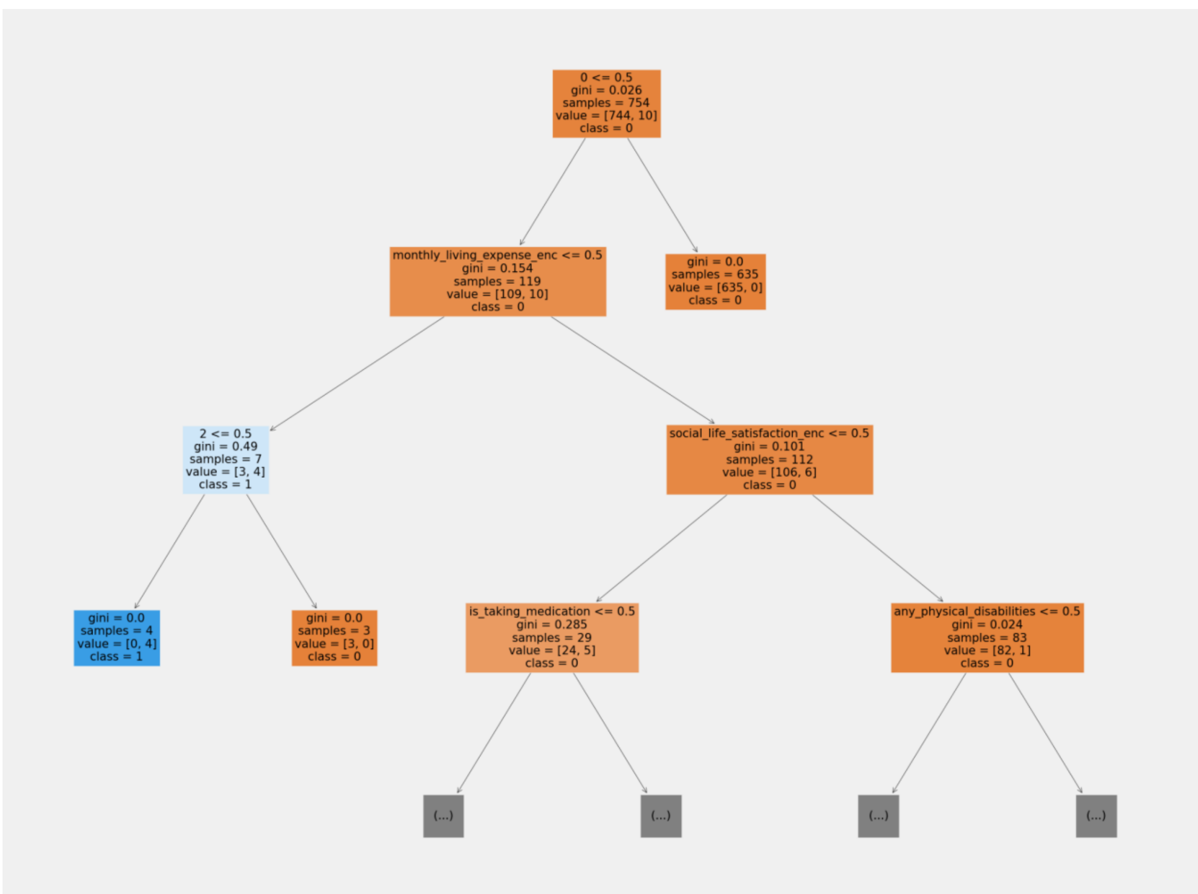

Figure 3.6: Tree created by DT classifier.

3.5.3 Random Forest (RF)

For this model, I imported the RandomForestClassifier from the sklearn.ensemble package. Remarkably, the accuracy reached 95.77%. The associated confusion matrix is visualized in Fig 3.7.

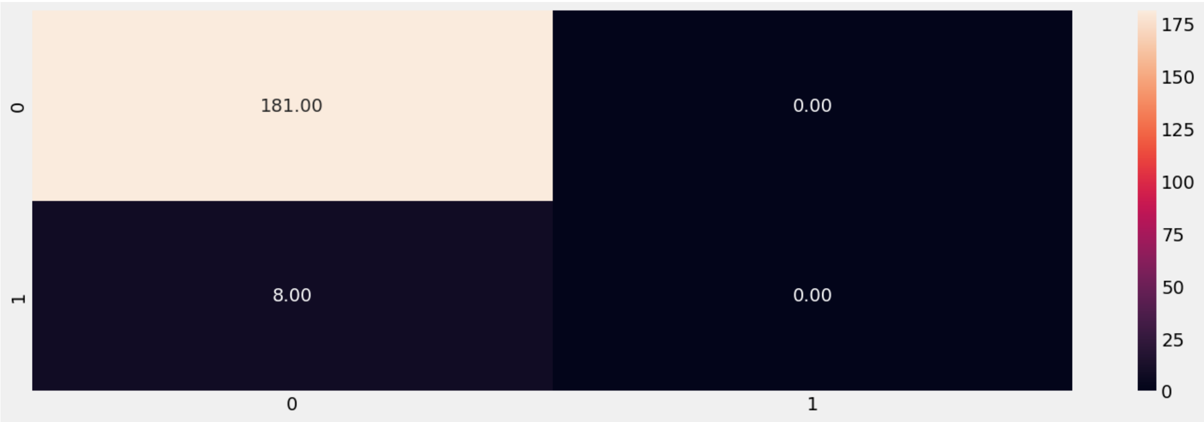

Figure 3.7: Confusion matrix for RF.

3.5.4 Gradient Boost (GB)

Utilizing the GradientBoostingClassifier from the sklearn.ensemble module, I achieved an accuracy of 95.77%. The associated confusion matrix is illustrated in Fig 3.8.

Figure 3.8: Confusion matrix for GB.

3.5.5 KNN

Following a splitting ratio of 3:1, I implemented the KNeighborsClassifier from the sklearn.neighbors module. The model achieved an accuracy of 97.46%, and the corresponding confusion matrix is presented in Fig 3.9.

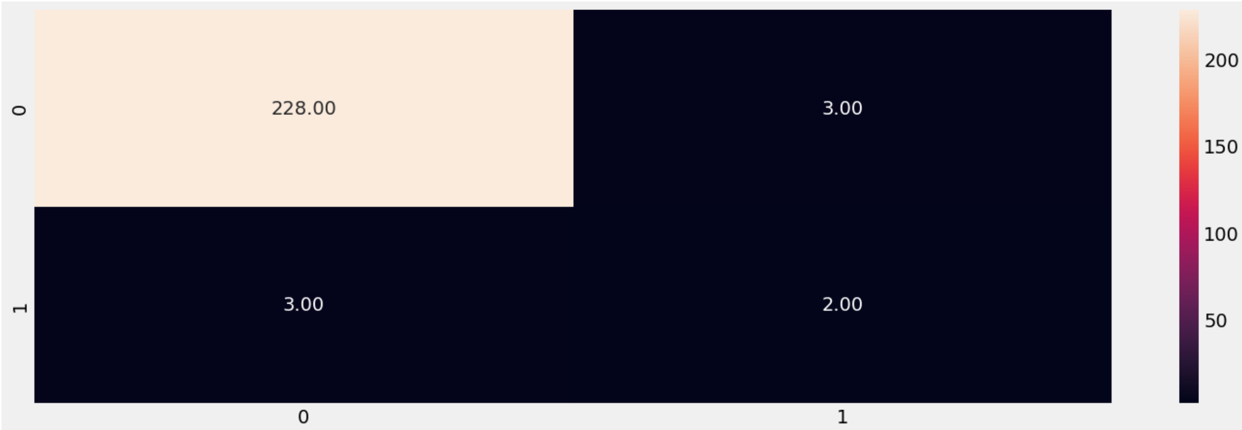

Figure 3.9: Confusion matrix for KNN.

3.5.6 Naive Bayes (NB)

Using the MultinomialNB from the sklearn.naive.bayes module with a splitting ratio 3:1, I achieved an accuracy of 97.03%. The confusion matrix is provided in Fig 3.10.

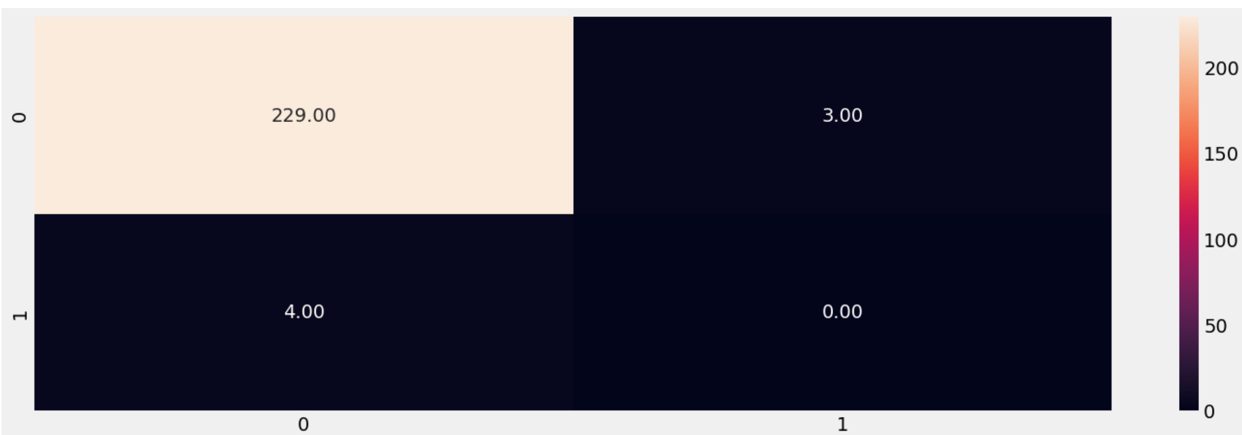

Figure 3.10: Confusion matrix for NB.

3.6 Implementation Requirements

Several critical elements must come together for the mental health detection paradigm to be implemented successfully. Above all, it requires a strong hardware foundation whose specs match the model's computational requirements. This involves taking memory, computing speed, and storage capacity into account.

At the same time, the software stack is essential. The model must function seamlessly with pre-specified libraries, frameworks, and programming languages. The software components—including versions and dependencies—essential to the model's operation are described in great depth in this section. The implementation journey explores any necessary third-party technologies or tools to deliver the model. This includes data pretreatment tools, user interfaces, and integration possibilities with current systems. To have a thorough comprehension, consult the approaches described in the preceding segments of this discussion.

Additionally, the section explores any third-party tools or technologies necessary for the model's deployment. This could include user interfaces, integration with current systems, and data preprocessing tools.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

In this section, I will provide an overview of the key components and objectives of the research, emphasizing the importance of addressing depression among university students in Bangladesh. The introduction sets the stage for the subsequent chapters, outlining the study's scope, motivation, and methodology.

The computational part was built on Google Colab, which provides cloud-based resources that are available. Python emerged as the primary programming language, exploiting its enormous libraries and frameworks. The foundation of mental health identification was created by the selected machine learning algorithm.

The selection of the dataset ensured alignment with the research objectives by focusing on. In calculation, hardware characteristics such as CPU, GPU, or TPU resources were vital. To maximize the efficiency of the research workflow, software tools for data pretreatment, model creation, and evaluation were carefully selected.

This part adds to the transparency and reproducibility of the research by narrating the essential components of the experimental setup.

4.2 Experimental Results & Analysis

The six implemented algorithms can be assessed and compared from various perspectives. One such evaluation is facilitated by the confusion matrix, which offers diverse insights into the algorithm's performance. For instance, examining the algorithm's precision, defined as the ratio of true positives (TP) to the sum of true positives and false positives (TP + FP), allows us to discern how accurately the model identified positive instances.

Finally, precision, recall, and F1 scores can be computed for each category within the target class, and the average and weighted average of these accuracy metrics can be determined. This section will assess and compare the accuracy score and classification report (precision, sensitivity, F1 score, etc.) for the six implemented algorithms. The analysis commences with comparing accuracy scores, specifically focusing on validation accuracy.

Among the implemented algorithms, the Random Forest and Gradient Boost exhibited the lowest accuracy at 95.77%. At the same time, the Logistic Regression, Decision Tree, Naive Bayes, and KNN achieved the highest accuracy of 97.88%, 97.35%, 97.03%, and 97.46%. Precision, sensitivity, and F1 scores are presented in tables organized by categories within the target class to evaluate the algorithms further.

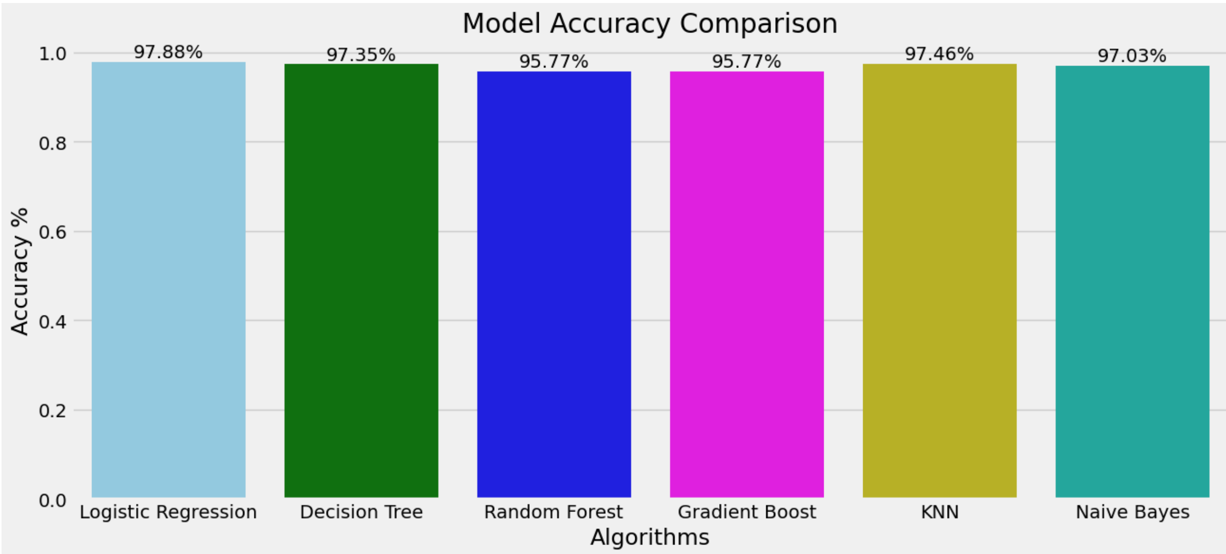

Figure 4.1: The accuracy of all proposed models

In Table 4.1, my attention shifts towards sensitivity, also called recall. This metric verifies the algorithm's proficiency in identifying positive instances within the designated target class. The emphasis on sensitivity highlights the algorithm's ability to capture and correctly classify relevant instances, providing valuable insights into its performance.

Furthermore, the table introduces the F1-score, a pivotal measure that calculates the harmonic mean of precision and sensitivity. This composite metric evaluates the algorithm's effectiveness, considering both precision (positive predictive value) and recall (sensitivity). Combining these aspects, the F1 score provides a balanced assessment, particularly valuable in scenarios where achieving a harmonious trade-off between precision and recall is crucial.

These meticulously crafted tables in Section 4.1 are valuable resources, offering a detailed breakdown of algorithm performance. They play a pivotal role in facilitating the assessment and comparison of the algorithms' effectiveness across diverse contexts. As a result, these tables contribute significantly to my understanding of how well the algorithms perform in different scenarios, enabling informed decision-making in machine learning evaluation.

These meticulously crafted tables serve as valuable resources for a detailed breakdown of algorithm performance, which is pivotal in assessing and comparing the algorithms' effectiveness in diverse contexts.

Table 4.1: Classification Report

Models Name	Accuracy	Precision	Recall	F1 Score
Logistic Regression	97.88%	98	98	97
Decision Tree	97.35%	97	97	97
Random Forest	95.77%	92	96	94
Gradient Boost	95.77%	92	96	94
KNN	97.46%	97	97	97
Naive Bayes	97.03%	97	97	97

4.3 Comparison with Other Works

Table 4.2: Comparison with Other Works

Reference	Year	Method	Accuracy	Findings
Determining Clinical Depression From TheAnalysis of Socio-Economic Attributes[10]	2020	KNN, Random Forest, Gradient Boost	83.52%, 83.8%, 80.45%	Accuracy can be enriched.
Depression screening using mobile phone usage metadata: a machine learning approach[11]	2019	Random Forest Classifier	81.1%	This research received no specific grant from any public, commercial, or not-for-profit sector funding agency.
Prevalence and predicting factors of perceived stress among Bangladeshi university students using machine learning algorithms[13]	2021	Random Forest, Logistic Regression	89.7%, 74.7%,	The study results reveal that university students' Pulse rate, SBP, DBP, and Sleep status, Smoking status, and Background were the major significant factors for their stress using the ML features selection algorithm—Boruta.
Detection of child depression using machine learning methods[18]	2021	Random Forest	95%	The RF model outperforms competitors in accurately predicting child and adolescent depression across all metrics and execution time, showcasing its effectiveness and efficiency.
Predicting Depression in Bangladeshi Undergraduates using Machine Learning[8]	2019	Random Forest, KNN	75%, 67%	Among the three algorithms tested, Random Forest emerges as the most effective, achieving a 75% accuracy and demonstrating potential for early

				detection and intervention in depressive cases.

4.4 Discussion

The results demonstrate how well machine learning algorithms detect depression in Bangladeshi university students. The 95.77% to 97.88% range for the models' overall accuracy shows how well they perform in binary classification.

All models had a consistently high level of precision, which measures the accuracy of positive predictions. This suggests that a model is probably accurate when it predicts depression. The model's sensitivity, which measures its capacity to detect positive examples, was likewise strong, reducing the possibility of overlooking actual positive situations.

The models achieved a compromise between capturing true positive cases and avoiding false positives, as demonstrated by the F1 score, which combined sensitivity and precision. Naive Bayes, KNN, Decision Tree, and Logistic Regression showed notable F1 scores.

When compared, the models with the highest accuracy and precision were Logistic Regression, Decision Tree, and Naive Bayes. KNN demonstrated good sensitivity and accuracy, making it a strong option for determining genuine positive cases. While Random Forest and Gradient Boost were marginally less accurate overall, they performed admirably.

It is imperative to recognize several limitations, including possible biases arising from the self-reported form of the dataset and the influence of cultural context on generalizability. Subsequent investigations may delve into supplementary characteristics and diverse demographics to augment the generalizability and efficacy of the model in tackling mental health issues among Bangladeshi university students.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

The study of depression among Bangladeshi university students has significant ramifications for the welfare of society. The knowledge and understanding gained from this research help the academic community become more mindful of mental health issues. The research has a significant impact on how society views mental health by bringing attention to the incidence and effects of depression.

The emphasis significantly impacts social norms around conversations about mental health on lowering stigma and encouraging candid communication. This change helps build a more understanding and encouraging society, where people are encouraged to ask for assistance without worrying about being judged. Long-term effects include fostering a culture that prioritizes mental health, enhancing interpersonal relationships, community dynamics, and the resilience of society as a whole.

5.2 Impact on Environment

The study supports long-term mental health support networks within academic settings. There are several effects on the academic environment that affect staff, teachers, and students' well-being. The study's conclusions promote the growth and improvement of mental health services in educational settings, creating a welcoming and encouraging atmosphere.

Universities' long-lasting mental health culture is built on raising awareness and implementing effective mental health programs. A psychologically sound academic community is better equipped to meet the varied requirements of its members, which enhances student achievement, raises satisfaction levels, and fosters a supportive work environment. Future generations of students will also be impacted as they stand to gain from an atmosphere that actively promotes mental health.

5.3 Ethical Aspects

The ethical aspects of this research have been of utmost importance. Participants' privacy and confidentiality have been scrupulously maintained. All participants provided informed consent, attesting to their voluntary involvement and comprehension of the study's objectives. The data collecting and analysis procedures were conducted honestly under ethical principles.

Additionally, by treating depression with empathy and delicacy, the study sought to reduce any possible harm to participants. Ethical communication techniques guide the distribution of research findings, ensuring that the material is communicated properly and does not further stigmatize or cause harm.

5.4 Sustainability Plan

The research's sustainability strategy calls for the academic community to continue advocating for and supporting mental health issues. The following tactics will be used to maintain the favorable effects on the environment and society:

- **Constant Awareness Campaigns:** To keep the stigma around mental health disorders low and build a network of support, ongoing campaigns will be held to raise awareness of these conditions.
- **Allocation of Resources:** The institutional commitment to continuously set aside funds to improve mental health initiatives, guaranteeing support networks' viability.
- Collaboration and Networking: Establishing partnerships with mental health providers, organizations, and community members to establish a network of resources and support.
- **Longitudinal Studies:** Using longitudinal research to monitor the success of mental health programs over time will enable the development of adaptable methods depending on changing requirements.
- **Education and Training:** Continuing education is essential to help university staff and faculty identify mental health issues and address them in a way that will support a long-lasting culture of caring.

The research intends to bring about long-lasting positive changes in society's perspective on mental health and to aid in establishing sustainable support networks within university environments by integrating these components into a holistic sustainability plan.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Research

The study effectively used machine learning algorithms to develop a prediction model to detect depression in Bangladeshi university students. The research, predicated on a painstakingly assembled dataset from anonymous surveys, concentrated on identifying and comprehending the fundamental causes of depression.

High F1 scores, sensitivity, accuracy, precision, and sensitivity were found for various machine learning models, including Gradient Boost, Decision Tree, Naive Bayes, KNN, Random Forest, and Logistic Regression. These findings highlight machine learning's potential to help university students with mental health issues.

The study advances my knowledge of mental health in the setting of higher education and promotes more candid discussions and preventative actions to improve the well-being of students. It lays the groundwork for upcoming initiatives and policy discussions focused on fostering an atmosphere that supports students' mental health in Bangladesh and other cultural contexts.

6.2 Conclusion

Using sophisticated machine learning algorithms and statistical models, my research has created an effective predictive model designed to identify depression among university students in Bangladesh. The model demonstrated commendable accuracy when applied to its training dataset. This dataset was meticulously crafted through the distribution of surveys among a wide-ranging group of university students in Bangladesh.

The overarching aim of my research is to enhance the well-being of students by addressing the underlying factors contributing to depression. Given the vulnerability of the youth in my country to this issue, it becomes paramount to tackle depression head-on and intensify my focus on the mental health of university students. My work is not only about detection but also about fostering a proactive approach to mitigate the impact of depression on the academic and personal lives of students.

6.3 Implications for Further Study

As with any research, there are avenues for future exploration and development. Some potential areas for future work include

- **Longitudinal Studies:** Conducting longitudinal studies to track the mental health of university students over an extended period can provide valuable insights into the dynamics of depression and its contributing factors.
- **Intervention Strategies:** Designing and implementing targeted intervention strategies based on the predictive model's findings can be a crucial next step. Evaluating the effectiveness of these interventions can contribute to ongoing improvements in mental health support.
- **Cross-Cultural Studies:** Extending the research to include cross-cultural studies can enhance my understanding of how cultural factors influence depression among university students.
- **Technological Advancements:** Keeping abreast of technological advancements in machine learning and data analytics to improve the accuracy and efficiency of depression detection models.

In conclusion, this research lays the foundation for addressing the pressing issue of depression among university students in Bangladesh, and future work can build upon these foundations to further advance mental health initiatives in educational institutions.

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PLAGIARISM REPORT

MENTAL HEALTH AMONG UNIVERSITY STUDENTS IN BANGLADESH IS FORECASTED USING MACHINE LEARNING

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