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Predicting Student Mental Health Using Machine Learning Approaches

Journal of Electrical Systems

***Abstract:* -** Concern over mental health issues among students has in- creased in the last few years. Academic stress, fears about the future, and social constraints can all negatively impact students' well-being. Early detection is necessary for effective support and intervention for mental health issues. Even though mental health is crucial for well-being, in countries like Bangladesh, where there are few community care facilities for psychiatric patients and the government only devotes 0.44% of the total health budget to mental health, it is not adequately re- searched and recognized as a serious public health concern. Furthermore, the fact that less than 0.11% of people have free access to psychotropic medicine suggests that there is a severe lack of mental health services. In this age of technology and data-driven decision-making, machine learning has emerged as a practical method for assessing and categorizing the mental health conditions of pupils. This research investigates the development of a predictive model that categorizes student mental health into three groups: "At Risk," "Healthy," and "Distressed" By utilizing machine learning for student mental health assessments, educational institutions and healthcare practitioners may tackle these problems in a whole new way, which will benefit students' overall wellbeing.

Keywords: Mental Health, Decision Tree, Linear Regression, Logistic Regression, ML, KNN, Naive Bayes.

I. Introduction

In Bangladesh, the issue of student mental health has received a lot of attention lately. Due to its vibrant culture and rapidly growing education sector, this South Asian nation is home to a large and diverse student population. Bangladesh's educational system is becoming more expansive and competitive, which presents a number of challenges for students to conquer and could be detrimental to their mental health. Bangladeshi students encounter numerous obstacles as a result of the confluence of societal norms, financial constraints, and the pursuit of academic excellence. The educational system is highly competitive, and students often feel a great deal of stress about their academics, especially before big exams like the Higher Secondary Certificate (HSC) and university entrance exams. In addition to the challenges that come with becoming an adult, social and familial expectations for success can cause anxiety and depression in students. In Bangladesh, receiving treatment for mental health issues is highly stigmatized, and access to mental health care is routinely restricted. Because of this stigma, students could be discouraged from asking for help when they most need it. In light of these challenges, classifying and predicting students' mental health using machine learning can offer a unique perspective. Using data-driven methods, like the machine learning models covered in this paper, can give a more complete view of the state of mental health in educational institutions. The goal of this project is to develop a machine learning model that can predict and classify the mental health of students into three distinct stages: "At Risk," "Healthy," and "Distressed." This strategy aims to provide medical professionals and educational institutions with the early warning system they need to intervene before mental health issues worsen.

Creating a culturally relevant early intervention approach is the aim, in addition to assessing the mental health of the students. This study can improve the general strategy for student welfare by developing prediction models to the specific local context and taking into account the particular difficulties faced by students. Through the use of machine learning to predict and classify mental health disorders, we can provide support before issues worsen, reducing the burden on students and the educational institutions they attend. Furthermore, this research can help

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develop targeted interventions and support services by offering a more detailed understanding of the factors influencing students' mental health. This discovery has implications for public health as well because it addresses a critical issue for the health of future generations. By addressing student mental health, we may be able to reduce the long-term burden on healthcare providers and society at large.

II. Related Works

There has been many studies and researches where people have been predicting mental health problems like depression and anxiety using the algorithms of machine learning, like decision tree, support vector machine, random forest and convolution neural network for the collection and classification of data from blog posts. Chung et al. (2023) wanted to empirically assess several well-known machine learning techniques, both from a single classifier approach and an ensemble ma- chine learning strategy, in order to categorize and forecast mental health difficulties based on a given data set. The data set contains the questionnaire responses from the Open Sourcing Mental Illness (OSMI) survey. This study looked at various machine learning methods, such as Support Vector Machine, Gradient Boosting, Neural Networks, K-Nearest Neighbors, Logistic Regression, and an ensemble approach that incorporated these algorithms. Furthermore, analyses were conducted using two more recent machine learning methods: Extreme Gradient Boosting and Deep Neural Networks. Gradient Boosting surpassed Neural Networks, which came in second with 88.00% overall accuracy, with an overall accuracy of 88.80%. Deep Neural Networks and Extreme Gradient Boosting followed at 86.40% and 87.20%, respectively. The ensemble classifier received 85.60%, whereas the other classifiers had scores between 82.40 and 84.00%. Furthermore, it was demonstrated that every machine learning method that was looked at in this article could produce prediction results that were more accurate than 80%.

The focus of Jage et al. (2023) research was on predicting mental health using deep learning methods and support vector machines. Support vector machines are utilized to solve the current problem, while various machine learning and deep learning techniques help to overcome these contemporary challenges. Support Vector Machines (SVM) outperforms other machine learning methods in terms of accuracy when predicting mental illness. Jain et al. (2021) recommended using a number of machine learning techniques, including logistic regression, naive bayes classifier, support vector ma- chines, decision trees, and K-nearest neighbor classifier, to ascertain the mental health condition of a target population. Initially, unsupervised learning methods were used for the target group's survey responses. The labels generated as a result of clustering were validated by calculating the Mean Opinion Score. After then, in order to predict a person's mental health, classifiers were built utilizing these cluster labels. A wide range of demographics were included in the target categories, such as high school students, college students, and working professionals. The paper examines how the previously mentioned machine learning algorithms are applied to the target demographics and makes recommendations for future research directions.

A variety of significant and well-known machine learning algorithms, including k-Nearest Neighbors (kNN), Random Forests (RF), Support Vector Ma- chines (SVM), and Linear Discriminant Analysis (LDA), were the subject of a 2021 study by Sahlan et al. The authors assessed many criteria in terms of generalization errors at different levels, including the number of features, training sample size, biological variation, experimental variation, effect size, replication, and correlation between features. They were able to accomplish this because to massively parallel processing on potent supercomputers. In terms of average generalization errors and stability (precision) of error estimations, LDA was determined to be the best technique for fewer correlated characteristics, which are defined as features that don't surpass roughly half the sample size. As the feature set grows, SVM (with RBF kernel) outperforms LDA, RF, and kNN by a significant margin, provided that the sample size is at least 20.As the number of features increases, kNN performs better than LDA and RF, unless the effect sizes are too small or the data variability is too great. It was found that when the data were more variable and had smaller impact sizes, RF outperformed just kNN in a number of scenarios. Furthermore, in these conditions, RF produces more precise error estimates than kNN and LDA.

In order to predict the state of student well-being, Laijawala et al. (2020) used a variety of machine learning algorithms based on information on university students' entrepreneurial ability. The findings show that a student's gender and major selection have a big influence on their overall wellbeing. With accuracy and F1-scores of 0.64 and 0.61, decision trees outperform KNN and SVM. Shafiee et al. (2020) developed a model that constructed expectation models using eight widely used machine learning calculation techniques: decision tree (DT), random forest (RF), support vector machine (SVM), naive Bayes (NB), logistic regression (LR), xGBoost (XGB), gradient boosting classifier (GBC), and artificial neural network (ANN). The model utilized a large dataset (1429 individual surveys). This led to accurate and fruitful dynamics. Various models and approaches have been employed in this study to acquire a clear and accurate image. The ultimate result of employing Support Vector Machine (SVM) was 87.38 percent. Srividya et al. (2018) selected five machine learning techniques and assessed each one's accuracy in recognizing mental health issues using a variety of ac- curacy metrics. The five machine learning techniques are Stacking, Random Forest, Decision Tree Classifier, K-NN Classifier, and Logistic Regression. We were able to ascertain which stacking technique-based prediction approach was the most accurate, with an accuracy of 81.75%, after comparing and utilizing several strategies. Khan et al. (2018) examined a method of classification for forecasting mental illnesses. The authors examined the datasets of 466 patients with mental diseases in order to determine the relationship between features and diagnosis. To diagnose mental health illnesses, they used three machine learning algorithms: Random forest, SVM, and K-nearest neighbor. Next, a comparison was made between the aforementioned algorithms' performances based on different accuracy standards. The studies' findings demonstrate that Random Forest performs better than the other algorithms. Using machine learning algorithms, Dobson et al. (2016) concentrated on classifying pupils with a range of mental health issues, such as stress, depression, and anxiety. Various techniques are used, including logistic regression, Naıve Bayes, decision trees, neural networks, and support vector machines. The most accurate models for stress, depression, and anxiety are decision trees, neural networks, and support vector machines, in that order. The decision tree model had the highest accuracy, at 84.44%. The objective of this research paper is to help people understand about their problems and give doctors an overview into their patient's psyche. All of this could only be possible when we use models with the most accuracy.

III. METHODOLOGY

The experimental technique has five primary phases: planning and background analysis, data collecting, data pre-processing, model implementation, and performance evaluation. To develop a mental health prediction model for students, these steps are carefully completed. 150 students' responses to surveys are gathered, processed, encoded, and prepared for analysis. Using machine learning techniques, the model is trained and evaluated to find out how well it categorizes students into various mental health disorders. The study emphasizes the significance of model correctness, interpretability, and practical value in addressing students' mental health issues.

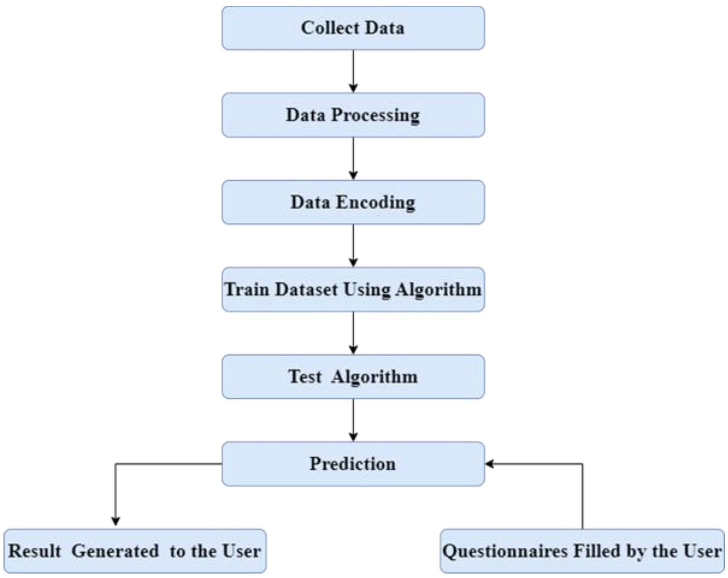

Figure 1. Working Methodology

The primary objective of this research is to develop a prediction model for student mental health assessments. Developing a model that can accurately categorize students into different mental health disorders is the aim. Specifically, the model will be used to categorize students as "Healthy" "At Risk," or "Distressed".

3.1 Data Collecting

The dataset for this study was compiled from surveys that 150 Bangladeshi students completed. Six primary categories are used to collect data: Academics, medical-history, Psychological, Social, Demographics, Lifestyle and Health Behavior. There are a total of 32 attributes, each of which highlights a distinct aspect of the students' lives. One of these traits serves as the objective variable and stands in for the mental well-being of the students. The data collection method was done very carefully to ensure accuracy and representatives. Participants' consent and privacy were given top priority during the data gathering process, and survey results were carefully documented.

3.2 Data Preprocessing

The data preprocessing is crucial to ensuring that the dataset is ready for analysis and modeling. This typically involves processing missing data, managing outliers, scaling numerical characteristics, and classifying categorical variables. But it's crucial to remember that this study's dataset was exceptionally clean and comprehensive. Since everyone who participated in the survey had to answer all of the questions, there were neither missing nor null values. As a result, handling missing data required less data preprocessing, enabling the data to be utilized straight away for the ensuing steps of analysis and modeling. In order to convert categorical variables into a numerical format suitable for machine learning, data encoding was a critical step in the data preprocessing procedure in this study. Figure 1 of Separate types of category data were managed using two separate encoding techniques:

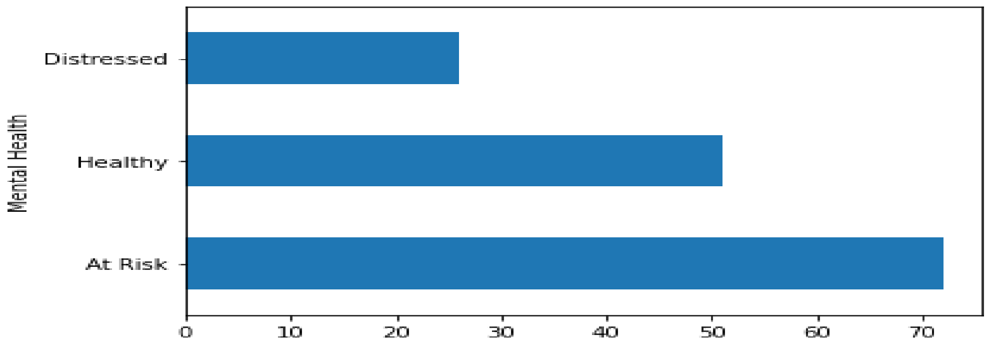

Figure 1:Class Label Status of Collected Data

Label Encoding: "Self-efficacy, self-esteem, gender, academic performance, attendance, engagement in studies, stress levels, Depression, PTSD, eating disorders, OCD, mood disorders, alcohol and drug abuse, and mental health are among the conditions that need to be addressed. Label encoding was chosen for these attributes because they display an ordinal connection in which one category can be thought of as "higher" or "worse" than another.

One-Hot Encoding: Encoding: 'Ethnicity,' 'Sexual Orientation,' 'Country,' 'City,' 'Department,' 'Relationship Status, "Personality Traits,' 'Coping Styles,' 'Social Interaction,' 'Peer Support,' 'Physical Activity,' 'Proper Sleep,' 'Screen Time,' 'Screen Time Focus,' 'Professional Help,' and 'Stress Source.' One-hot encoding creates binary columns for each category to guarantee that there isn't any implied hierarchical link between them. The dual encoding approach was chosen to make sure the dataset was appropriately prepared for the upcoming stages of the study and implementation of machine learning models. It maintains the in- dependence of some attributes while maintaining the meaningful order in others.

3.3 Model Implementation

To ensure the best possible working of machine learning algorithms it needs to work with some key parameters. Each and every task requires a different model based on the type of data and work is being dealt with. Hence, it is crucial to adjust the model's parameters to increase its utility and accuracy. In our work in Figure 2, we have tried to ensure to tune all the models with adequate parameter values and plump for the foremost value for our models. We outline how machine learning techniques can be used to identify student Mental Health. The five techniques that we will look at are decision trees, logistic regression, K-Nearest Neighbors (KNN), linear regression, and naive Bayes.

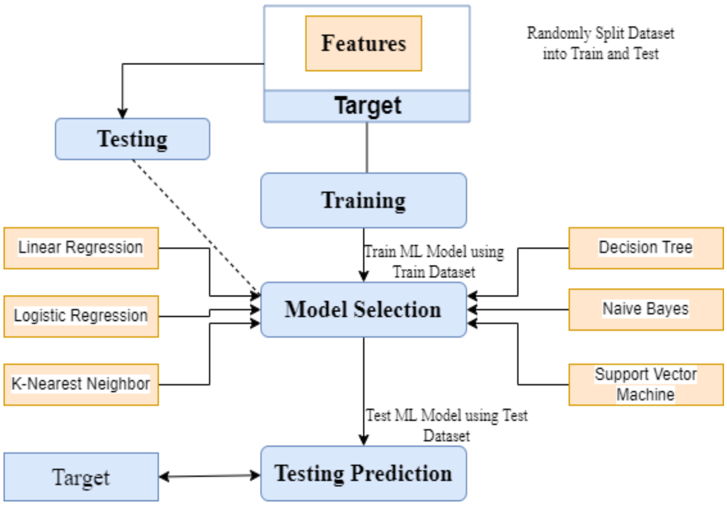

Figure 2. Framework of Model Implementation

Linear Regression: The objective of linear regression is to establish a linear relationship between the independent variable(s) and the dependent variable, "Mental Health".

$$MentalHealth = 0 + \beta 0 + \beta 1X1 + \beta 2X2 + . . . + \beta nXn \qquad (1)$$

I. Mental Health: The dependent variable representing the stage of Mental health.
II. B0: The intercept term.
III. B1,B2,Bn: The independent variables' coefficients.
IV. X1,X2,Xn: The independent variables like academic success, stress levels, etc.

Student Mental health can be predicted using linear regression by simulating the linear correlations between numerous variables, such as academic performance, stress levels, and self-esteem. The coefficients, or B values, show the strength and direction of these relationships.

Logistic regression: Logistic regression models the probability that an event (in this case,Mental Health) will occur using a logistic function:

$$P\ (MentalHealth) = \frac{1}{1+e-\beta 0 + \beta 1\ X1 + \beta 2X2 + \ldots + \beta nXn}$$

(2)

I. P(Mental Health): Indicates the probability of depression risk.
II. Mental Health: The dependent variable representing the stage of Mental health.
III. B0: The intercept term.
IV. B1,B2,Bn: The independent variables'coefficients.
V. X1,X2,Xn: The independent variables like academic success, stress levels, etc.

Using categorization, such as estimating the probability that a student will experience distressed or healthy mental health based on a number of factors, logistic regression can be used. It provides probabilities that which class of mental health may occur.

K-Nearest Neighbors (KNN): KNN lacks a particular equation, unlike lo- gistic or linear regression. Data points are classified according to the majority class among their K nearest neighbors, which is the basic concept of how it operates.KNN can be used to forecast student mental health by taking into consideration the mental health status of students with similar characteristics (features).Instead of a mathematical computation, it depends on the proximity of data points in a feature space.

$$A = (a1, a2, . . . , an) \ \text{and} \ B = (b1, b2, . . . , bn)$$

(3)

$$d = \sqrt{\sum_{i=1}^{n} \frac{(a_i - b_i)^2}{R_i{}^2}} = \sqrt{\frac{(a_1 - b_1)^2}{R_1{}^2} + \frac{(a_2 - b_2)^2}{R_2{}^2} + \cdots + \frac{(a_n - b_n)^2}{R_n{}^2}}$$

(4)

Decision Tree: Decision Trees are represented as a structure with nodes, branches, and leaves. Each node represents a choice based on an attribute, and each leaf node represents a class label (Healthy,At risk or Distressed).Decision trees can be used to predict student mental health by recursively segmenting the dataset depending on variables like stress levels, academic performance, and other char- acteristics. As a result, a tree that forecasts mental health states is produced.

$$Gini(P) = \sum_{i=1}^{n} P_i\,(1 - P_i) = 1 - \sum_{i=1}^{n} (p_i)^2$$

(5)

Naive Bayes: Naive Bayes uses Bayes' theorem to calculate the likelihood of a specific class (Healthy,At risk or Distressed) given the values of multiple inde- pendent factors.

$$P\ (DistressedX1,\ X2,\ ...,\ Xn) = \frac{p(X1Distressed)P\ (X2Distressed)\ldots P(XnDistressed)}{P(X1)P(X2)\ldots P(Xn)}$$

(6)

I. P(Distressed—X1, X2, Xn): The probability of distressed risk on the given values of the independent variables.

II. P(Xi—Distressed):The probability that Distressed will be experienced given a value of the i'th independent variable.

III. P(Distressed): The prior probability of Distressed.

Naive Bayes can be used to predict student Mental health by estimating the chance of distress based on the values of multiple independent parameters, such as personality traits, relationship status, and stress levels

IV. EXPERIMENTAL RESULT ANALYSIS

The table 1 displays the accuracy with which different machine learning approaches forecast and classify students' mental health. The accuracy scores show how well each approach does at correctly categorizing students into the"Healthy," "At Risk," and "Distressed" groups. A fundamental metric of a machine learning model's accuracy is how well it predicts the target variable on a held-out test set. In this case, the accuracy of each model was calculated as the number of accurate predictions divided by the total number of predictions.

Table 1. Predictive Model Metrics

Method	Accuracy
Linear Regression	66.54
Logistic Regression	72.13
KNN	80.0
Decision Tree	93.03
Naive Bayes	84.33
Random Forest	96.66
ExtraTreesClassifier	90.00

Linear Regression provides the relationship between one or more predictor variables and a continuous target variable is done through supervised learning with linear regression.

Table 2. Train and Testing R-Score

Algorithm Name	**Training R^2 score**	**Testing R^2 score**
Linear Regression	1.0	.5525
Logistic Regression	1.0	0.7212
KNeighborsRegressor	0.3055	0.1317
DecisionTreeRegressor	1.0	1.0
GaussianNB	0.8356	0.6167
RandomForestClassifier	1.0	0.7212
ExtratreeClassifier	1.0	0.7212

In predicting student mental health using various machine learning algorithms, the performance of these models can be assessed through their training and test R^2 scores in Table 2. Linear Regression achieves a perfect R^2 score of 1.0 on training data, but its test R^2 drops significantly to 0.5525, indicating possible over fitting. Logistic Regression and RandomForestClassifier both exhibit perfect performance on training data with a 1.0 R^2, and maintain reasonable generalization on test data with scores of 0.7212, suggesting better robustness. The KNeighborsRegressor, however, performs poorly on both training (0.3055) and test data (0.1317), indicating it's not well-suited for this prediction task.

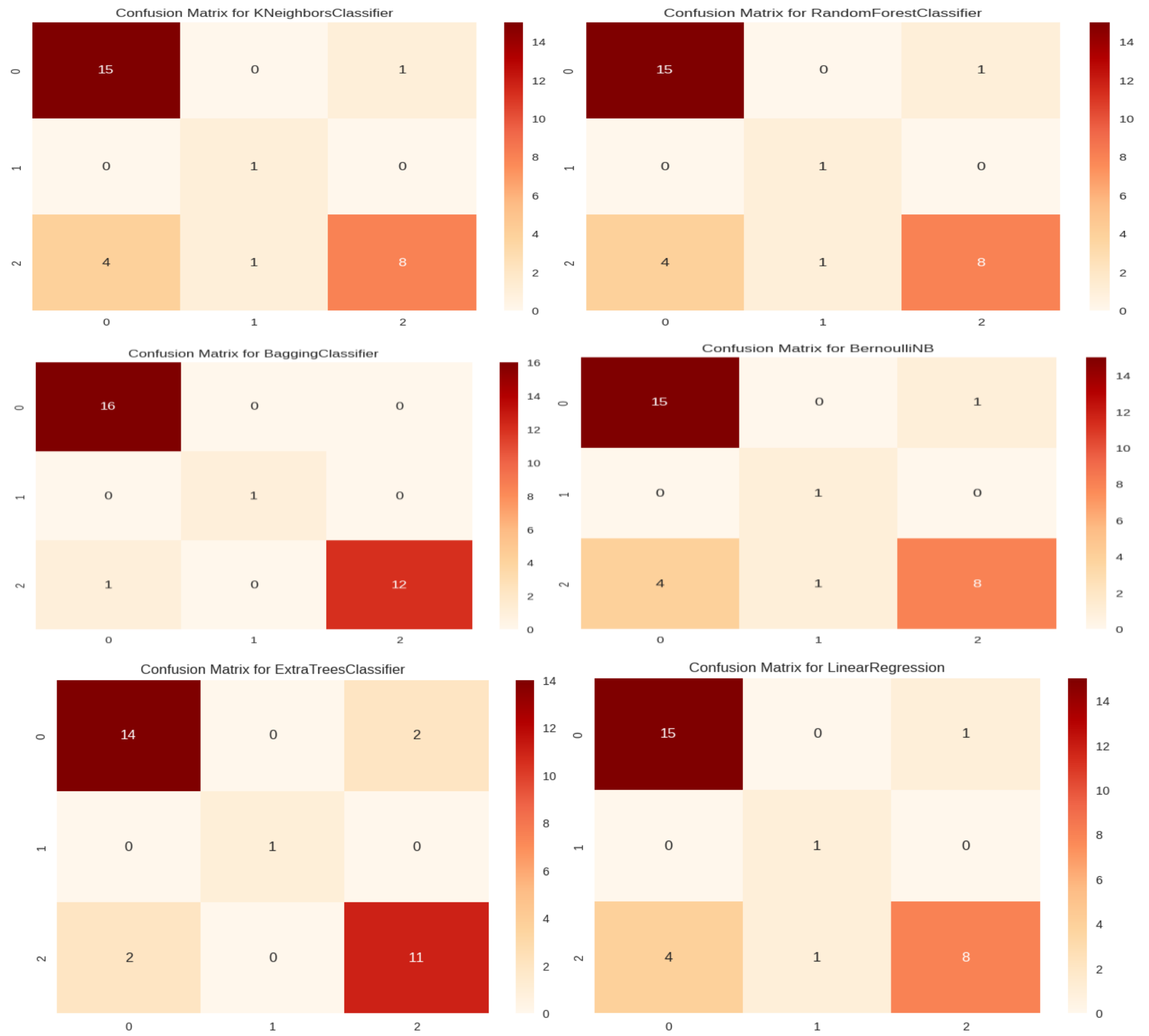

Figure 3. Graphical Representation of Confusion Matrix

DecisionTreeRegressor perfectly fits both training and test sets with 1.0 R^2, though this may suggest over fitting due to its ability to memorize the training data. GaussianNB shows decent performance with training and test scores of 0.8356 and 0.6167, respectively, demonstrating reasonable generalization. The ExtratreeClassifier, similar to Logistic Regression and RandomForestClassifier, maintains a perfect training score but a lower test score (0.7212), showing it can generalize relatively well to unseen data.

Table 3. Predictive Model Metrics

Model Name	Actual Result	Predicted Result
Logistic Regression	0 0 1 2 1 2 2 2 0 1 0 1 0 22 1 2 0 2 0 0 1 1 1 1	0 0 2 2 1 2 2 2 0 1 0 2 0 22 1 2 0 2 0 0 2 1 2 1
KNN	0 0 1 2 1 2 2 2 0 1 0 1 0 22 1 2 0 2 0 0 1 1 1 1	0 0 2 2 1 2 2 2 0 1 0 2 0 22 1 2 0 2 0 0 2 1 2 1
Decision Tree	0 0 1 2 1 2 2 2 0 1 0 1 0 22 1 2 0 2 0 0 1 1 1 1	0 0 2 2 2 2 0 2 2 2 0 2 0 22 2 2 0 2 0 0 2 2 2 2
Random Forest	0 0 1 2 1 2 2 2 0 1 0 1 0 22 1 2 0 2 0 0 1 1 1 1	0 0 2 2 1 2 2 2 0 1 0 2 0 22 2 2 0 2 1 0 2 2 2 2
Naive Bayes	0 0 1 2 1 2 2 2 0 1 0 1 0 22 1 2 0 2 0 0 1 1 1 1	0 0 2 2 2 2 2 2 0 2 0 2 0 22 0 2 0 2 0 0 2 0 2 2
Linear Regression	0 0 1 2 1 2 2 2 0 1 0 1 0 22 1 2 0 2 0 0 1 1 1 1	0 0 2 2 2 2 2 2 0 2 0 2 0 22 0 2 0 2 0 0 2 0 2 2

The accuracy scores in Figure 4 provide valuable insights into how effectively each method classifies students' mental health. The Random Forest model is the most accurate option for this task out of all the approaches tested where accuracy is 96.66%. This suggests that, for this particular prediction model, the Random Forest model is the best method of action because it does a remarkable job of accurately classifying students into the ”Healthy,” ”At Risk,” and ”Distressed” categories.

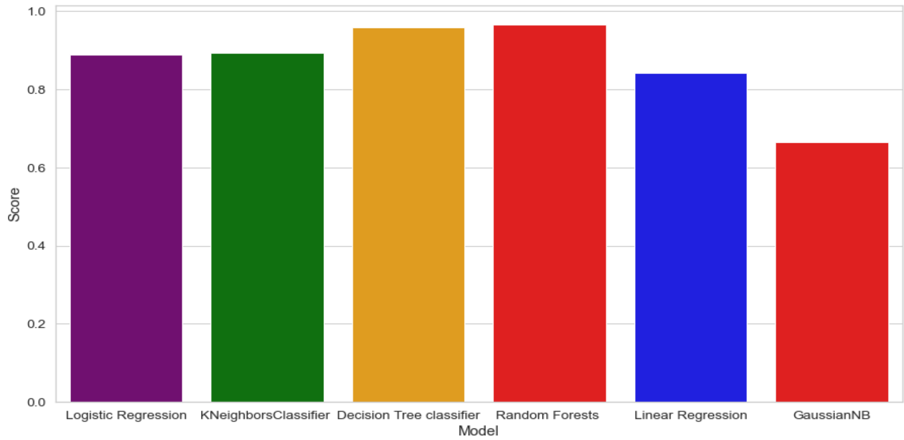

Figure 4. Graphical Representation of Applied Model

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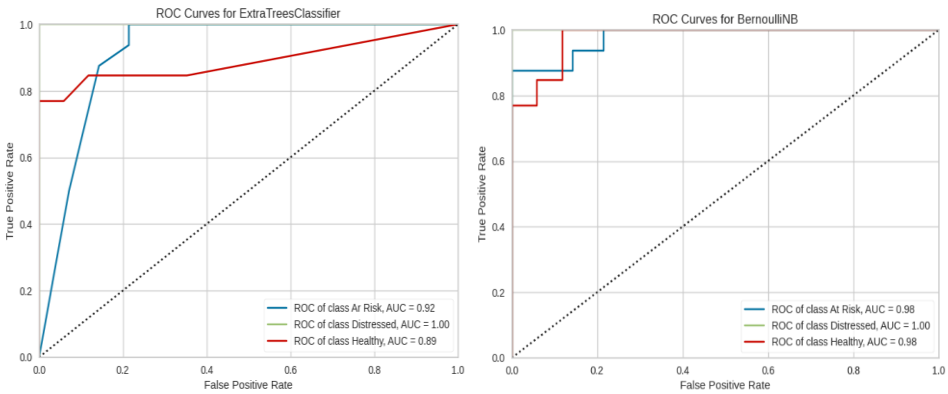
The ROC curves in Figure 5 compare the performance of several machine learning models—ExtraTreesClassifier, BernoulliNB, RandomForestClassifier, Bagging Classifier, and KNeighborsClassifier—in predicting student mental health categories: "At Risk," "Healthy," and "Distressed." The AUC for the "At Risk" group (labeled as "Not Accepted") is consistently 1.0 across all models, demonstrating perfect classification. For the "Healthy" group ("Accepted"), the AUCs vary, with ExtraTreesClassifier showing strong performance at 0.92, while Bagging Classifier achieves 1.0, and KNeighborsClassifier drops slightly to 0.90. The "Distressed" category ("May Be") sees the most variability, with AUCs ranging from 0.89 to 0.98, indicating slightly lower, but still solid classification. Overall, the Bagging Classifier excels across all categories, while the KNeighborsClassifier has a slight dip in performance for "Healthy" and "At Risk" students. BernoulliNB stands out for offering the most balanced classification across all groups.

In predicting student mental health using machine learning approaches, several key factors stand out. Post-Traumatic Stress Disorder (PTSD) and mood disorders, such as bipolar disorder, can significantly affect a student’s emotional and cognitive well-being, leading to challenges in managing stress and academic pressure. Sleep quality is another critical indicator, as inadequate or poor sleep can exacerbate symptoms of mental health disorders, contributing to issues like anxiety and depression. Depression itself is a prevalent mental health concern among students, often influencing motivation, social interactions, and academic performance. Age is also a relevant factor, as mental health challenges may vary across different stages of adolescence and adulthood, impacting how students cope with their environment and stressors. Understanding the interplay of these factors allows for more accurate and nuanced predictions of student mental health outcomes through machine learning models.



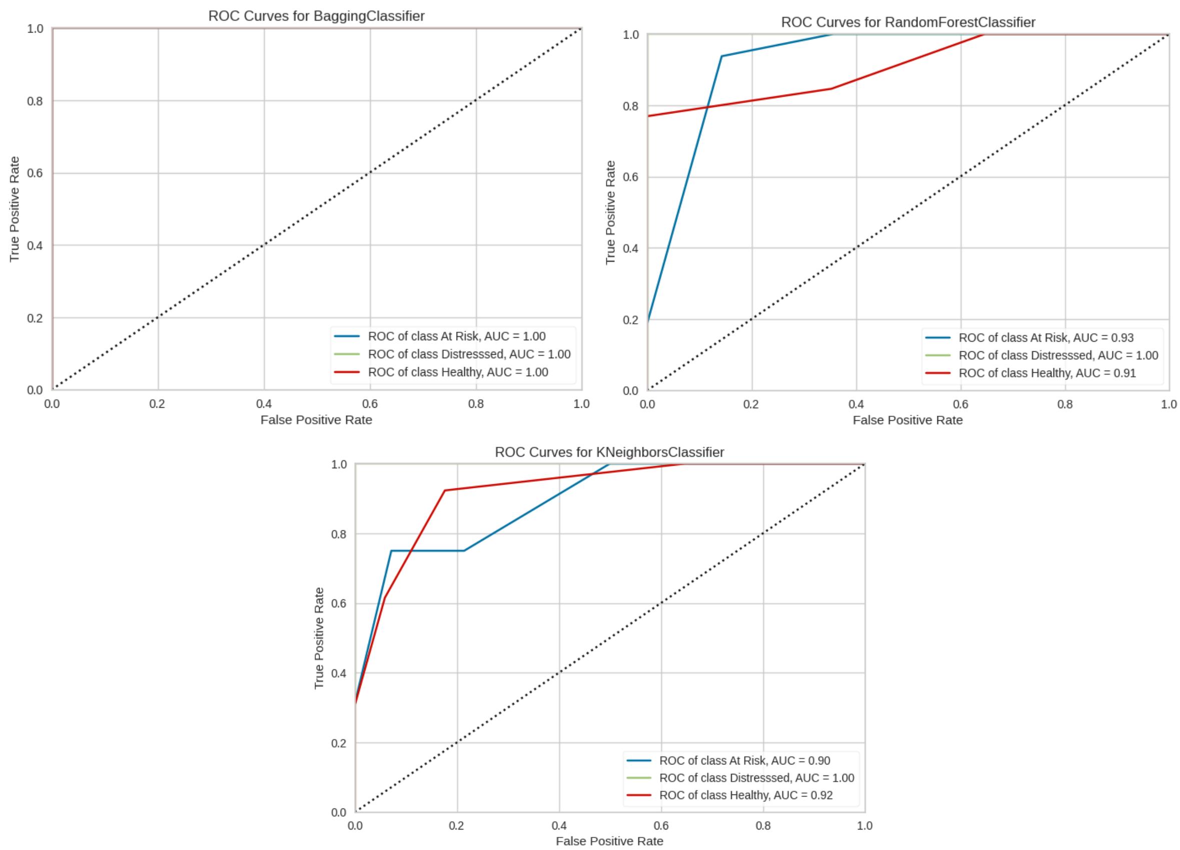


Figure 5.Roc Curve of Applied Algorithm

V. CONCLUSION

In conclusion, this study has laid the groundwork for Bangladeshi students' mental health to be predicted. Using a dataset of survey responses, machine learning algorithms have created a promising model that might be used to categorize students into three different mental health states: ”Healthy,” ”At Risk,” and ”Distressed “It is crucial to emphasize how this method can assist students who are experiencing mental health problems in a timely way, even with the small sample size. This study is just the beginning, underscoring the need for additional investigation, better models, and continued data collection. This study is a major step forward in the ongoing effort to have a complete understanding of Bangladeshi students' mental health.

VI. LIMITATION AND FUTURE WORK

There are some significant limitations to be aware of, even if this study offers relevant information on forecasting students' mental health. One of these is the extremely tiny dataset consisting of only 150 survey responses, which may limit the model's applicability in other contexts. Furthermore, there's a possibility that response bias will be created because the data is dependent on self- reporting, which would diminish the validity of mental health assessments. To further enhance the model's reliability, further studies ought to endeavor to augment the dataset's magnitude and incorporate diverse data sources. Future studies in this field should primarily concentrate on the limits that have been dis- covered. This necessitates the exploration of strategies for minimizing response bias and larger-scale data collection projects in order to strengthen the model's robustness. Further investigation may focus on developing increasingly extensive machine learning models and integrating relevant variables. Studies with long-term planning have the advantage of being able to track changes in mental health over time and offer an in-depth understanding of the changing mental health of Bangladeshi students.

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References

[1] K. Rasheed et al., "Machine Learning for Predicting Epileptic Seizures Using EEG Signals: A Review," in IEEE Reviews in Biomedical Engineering, vol. 14, pp. 139-155, 2021, doi: 10.1109/RBME.2020.3008792.

[2] Y. Zhu, Y. Shang, Z. Shao and G. Guo, "Automated Depression Diagnosis Based on Deep Networks to Encode Facial Appearance and Dynamics," in IEEE Transactions on Affective Computing, vol. 9, no. 4, pp. 578-584, 1 Oct.-Dec. 2018, doi: 10.1109/TAFFC.2017.2650899.

[3] F. J. Martinez-Murcia, A. Ortiz, J. -M. Gorriz, J. Ramirez and D. Castillo-Barnes, "Studying the Manifold Structure of Alzheimer's Disease: A Deep Learning Approach Using Convolutional Autoencoders," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 1, pp. 17-26, Jan. 2020, doi: 10.1109/JBHI.2019.2914970.

[4] A. Shahidi Zandi, R. Tafreshi, M. Javidan and G. A. Dumont, "Predicting Epileptic Seizures in Scalp EEG Based on a Variational Bayesian Gaussian Mixture Model of Zero-Crossing Intervals," in IEEE Transactions on Biomedical Engineering, vol. 60, no. 5, pp. 1401-1413, May 2013, doi: 10.1109/TBME.2012.2237399.

[5] Jain, T., Jain, A., Hada, P. S., Kumar, H., Verma, V. K., Patni, A. (2021, September). Machine Learning Techniques for Prediction of Mental Health. In 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 1606-1613). IEEE.

[6] S. Taylor, N. Jaques, E. Nosakhare, A. Sano and R. Picard, "Personalized Multitask Learning for Predicting Tomorrow's Mood, Stress, and Health," in IEEE Transactions on Affective Computing, vol. 11, no. 2, pp. 200-213, 1 April-June 2020, doi: 10.1109/TAFFC.2017.2784832.

[7] M. M. Aldarwish and H. F. Ahmad, "Predicting Depression Levels Using Social Media Posts," 2017 IEEE 13th International Symposium on Autonomous Decentralized System (ISADS), Bangkok, Thailand, 2017, pp. 277-280, doi: 10.1109/ISADS.2017.41.

[8] L. Nie, L. Zhang, L. Meng, X. Song, X. Chang and X. Li, "Modeling Disease Progression via Multisource Multitask Learners: A Case Study With Alzheimer's Disease," in IEEE Transactions on Neural Networks and Learning Systems, vol. 28, no. 7, pp. 1508-1519, July 2017, doi: 10.1109/TNNLS.2016.2520964.

[9] B. Wang, W. Kong, H. Guan and N. N. Xiong, "Air Quality Forecasting Based on Gated Recurrent Long Short Term Memory Model in Internet of Things," in IEEE Access, vol. 7, pp. 69524-69534, 2019, doi: 10.1109/ACCESS.2019.2917277.

[10] H. Tanaka et al., "Detecting Dementia Through Interactive Computer Avatars," in IEEE Journal of Translational Engineering in Health and Medicine, vol. 5, pp. 1-11, 2017, Art no. 2200111, doi: 10.1109/JTEHM.2017.2752152.

[11] K. Zhao and H. -C. So, "Drug Repositioning for Schizophrenia and Depression/Anxiety Disorders: A Machine Learning Approach Leveraging Expression Data," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 3, pp. 1304-1315, May 2019, doi: 10.1109/JBHI.2018.2856535.

[12] S. Ghosh and T. Anwar, "Depression Intensity Estimation via Social Media: A Deep Learning Approach," in IEEE Transactions on Computational Social Systems, vol. 8, no. 6, pp. 1465-1474, Dec. 2021, doi: 10.1109/TCSS.2021.3084154.

[13] M. Liu, J. Zhang, C. Lian and D. Shen, "Weakly Supervised Deep Learning for Brain Disease Prognosis Using MRI and Incomplete Clinical Scores," in IEEE Transactions on Cybernetics, vol. 50, no. 7, pp. 3381-3392, July 2020, doi: 10.1109/TCYB.2019.2904186.

[14] M. Lussier et al., "Early Detection of Mild Cognitive Impairment With In-Home Monitoring Sensor Technologies Using Functional Measures: A Systematic Review," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 2, pp. 838-847, March 2019, doi: 10.1109/JBHI.2018.2834317

[15] Chung, J., Teo, J. (2023). Single classifier vs. ensemble machine learning approaches for mental health prediction. Brain informatics, 10(1), 1-10.

[16] Bieli´nski, A., Rojek, I., Miko lajewski, D. (2023). Comparison of Selected Machine Learning Algorithms in the Analysis of Mental Health Indicators. Electronics, 12(21), 4407.

[17] Sahlan, F., Hamidi, F., Misrat, M. Z., Adli, M. H., Wani, S., Gulzar, Y. (2021). Prediction of mental health among university students. International Journal on Perceptive and Cognitive Computing, 7(1), 85-91.

[18] Laijawala, V., Aachaliya, A., Jatta, H., Pinjarkar, V. (2020, June). Classification algorithms based mental health prediction using data mining. In 2020 5th international conference on communication and electronics systems (ICCES) (pp. 1174-1178). IEEE.

[19] G. Han, W. Liu, X. Huang and B. Borsari, "Chain-of-Interaction: Enhancing Large Language Models for Psychiatric Behavior Understanding by Dyadic Contexts," 2024 IEEE 12th International Conference on Healthcare Informatics (ICHI), Orlando, FL, USA, 2024, pp. 392-401, doi: 10.1109/ICHI61247.2024.00057.

[20] O. S. Liang, C. C. Yang, K. Gliske, J. Braughton and Q. Ngo, "Visualizing Model Behaviors for Clinic Users: Explaining A Clinical Prediction Model for 30-day Readmission after Inpatient Alcohol Dependence Treatment," 2024 IEEE 12th International Conference on Healthcare Informatics (ICHI), Orlando, FL, USA, 2024, pp. 718-724, doi: 10.1109/ICHI61247.2024.00114.

[21] S. Merat and W. Almuhtadi, "Innovative Application of a Sleepwalking-Based Artificial Neural Model for Cybersecurity Risk Assessment," 2024 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 2024, pp. 1-8, doi: 10.1109/ICCE59016.2024.10444222.

[22] Jage, S., Chaudhari, S., Jatte, M., Mhatre, A., Mane, V. (2023, August). Predicting Mental Health Illness using Machine Learning. In 2023 3rd Asian Conference on Innovation in Technology (ASIANCON) (pp. 1-5). IEEE.