Original Article

Comparison of the Performance of Machine Learning-based Algorithms for Predicting Depression and Anxiety among University Students in Bangladesh: A Result of the First Wave of the COVID-19 Pandemic

Abstract

Introduction: The purpose of this research was to predict mental illness among university students using various machine learning (ML) algorithms. **Methods:** A structured questionnaire-based online survey was conducted on 2121 university students (private and public) living in Bangladesh. After obtaining informed consent, the participants completed a web-based survey examining sociodemographic variables and behavioral tests (including the Patient Health Questionnaire (PHQ-9) scale and the Generalized Anxiety Disorder Assessment-7 scale). This study applied six well-known ML algorithms, namely logistic regression, random forest (RF), support vector machine (SVM), linear discriminate analysis, K-nearest neighbors, Naïve Bayes, and which were used to predict mental illness among university students from Dhaka city in Bangladesh. **Results:** Of the 2121 eligible respondents, 45% were male and 55% were female, and approximately 76.9% were 21–25 years old. The prevalence of severe depression and severe anxiety was higher for women than for men. Based on various performance parameters, the results of the accuracy assessment showed that RF outperformed other models for the prediction of depression (89% accuracy), while SVM provided the best result than other models for the prediction of anxiety (91.49% accuracy). **Conclusion:** Based on these findings, we recommend that the RF algorithm and the SVM algorithm were more moderate than any other ML algorithm used in this study to predict the mental health status of university students in Bangladesh (depression and anxiety, respectively). Finally, this study proposes to apply RF and SVM classification when the prediction of mental illness status is the core interest.

Keywords: *Anxiety, Bangladesh, COVID-19, depression, machine learning algorithm, psychological*

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Introduction

COVID-19 started as a local transmission from the Wuhan city of China and has become one of the major calamities of the century.[1,2] From the earlier status of a global health emergency, the WHO officially certified COVID-19 as a "pandemic" on February 11, 2020 (WHO, 2020). Societies are facing great uncertainty considering the knowledge being developed about the unpredictable nature of the spread of this virus and its reciprocation with societal responses.[3,4]

Mental illness is also increasing at an epidemic rate worldwide, which was severe due to fear of COVID-19.[5,6] Some recent studies have shown that sociodemographic, behavior, and education are the main influencing factors for mental illness, including gender, residence, relationship status, socioeconomic status, and loneliness, personal autonomy, and future plans.[7-11] From a mental health standpoint, due to COVID-19, the world population have impacted not only by anxiety and trauma but also from unfavorable societal dynamics. Taking into account the current COVID-19 pandemic, numerous universities across the world have either held over or canceled all their campus activities. Universities have shifted their programs from the face-to-face to online system.[12,13] During quarantined and outside from university environment and schedule, students may encounter stress, anxiety, anger, boredom, loneliness and other emotions, which have both shorter and longer-term psychological impacts on health.[14-16] It affects the student's energy level, concentration, reliability, mental ability and optimism, thereby affecting student performance.[15,16]

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The Government of Bangladesh declared a public holiday on March 26, 2020, to lessen the transmission of COVID-19.[16] Since then, all the schools, colleges, and universities were closed, hampering the students' studies, daily routines, and daily habits, which in turn affecting their mental health. Furthermore, home quarantine, maintaining physical distance, and other restrictions also psychologically affected students and hindered their mental well-being.[17,18] On top of that, unpredictable situation, news, rumors, and misinformation can also raise negative thoughts within university students about their future.[19,20] All of this together can bring hopelessness, fear of death, and frustration among quarantined students.[19]

Before COVID-19, mental health studies reported an elevated level of moderate to extremely severe depression (52.2%), anxiety (58.1%), and stress (24.9%) among university students in Bangladesh.[21] Yet very little information is available on the mental situation of students during the COVID-19 pandemic, and so acquiring structured measures of depression, anxiety, stress can help to estimate the necessity for interventions to diminish the mental health impacts of the pandemic on students.

Mental health is an indicator of a person's emotional, psychological, and social well-being. There are many causes of mental illness (depression and anxiety). Academic performance, occupational status, and family status are considered the most important factors leading to depression and anxiety. Furthermore, previous investigations found that different variables, for example, sex, age, marital status, were significant factors related to depression and anxiety status.[7-10] In addition to proper diagnosis and intervention with mental health reduces the risk for depression and anxiety. Various statistical methods have been used to evaluate the mental health status of university students. The main objective of an estimation procedure is the correct prediction of depression and anxiety status using a machine learning (ML) algorithm. ML, a scientific method that intersects artificial intelligence and statistical learning research, may be how much knowledge can be researched to look for unknown associations or trends.[22] ML algorithms that can build models for prediction purposes have shown excellence in taking care of classification problems, in comparison to the classical statistical model. Furthermore, within the field of health and medical research, ML has become common.[23]

Many researchers have used ML algorithms such as random forest (RF) trees, support vector machines (SVMs), and convolutional neural networks to predict anxiety and depression.[24] In Sau *et al*.'s study, different ML algorithms such as logistic regression (LR), Catboost, Naïve Bayes (NB), RF, and SVM were used for classification.[25] In addition, ML can be used to better predict the risk of depression and anxiety. Therefore, the purpose of this study is to compare the prediction performance of six well-known ML algorithms such as LR, RF, SVM, linear discriminate analysis (LDA), K-nearest neighbors (KNN), and NB have been applied to predict mental health status (depression and anxiety) among university students in Bangladesh.

Methods

Participants and procedure

The research was a prospective cross-sectional survey, and the data was collected through an online questionnaire survey using a Google form. This self-administered rapid online survey was conducted between August 2020 and September 2020. Both public and private university students operating in Dhaka city and those who have an internet facility were able to respond to the questionnaire and were eligible for this analysis. To fulfill the objective, a structured questionnaire was designed by the authors, and the questionnaire was arranged into a "Google Form" by collecting highly pertinent facts about mental health and then it was sent to various public and private university students through social media and asked them to convey their informative responses.

A multistage sampling technique was applied for this study. In the first stage, 4 universities (two public and two private universities, respectively) were chosen randomly from Dhaka city. In the second stage, six departments were chosen from each of the selected universities. In the third stage, 100 students were randomly chosen from each of the selected departments from the 1st year to the 5th year (additionally, graduate students for some departments). Here students were numbered consecutively each year as per their ID numbers. From this design, a total of 2400 students were selected for an interview and out of this 2350 consented. From the 2350 respondents, a total of 2121 students were found who had answered the structured questionnaire through "Google Form" and valuable information was stored precisely. In this case, the study sample size was 2121 and the response rate was 90.25%. Almost 10% of the students did not participate in this study after knowing the consent information. Among the students, 55.1% were women and 44.9% were men. In this analysis, the students came from all over Bangladesh and could be representative of the entire population.

Ethical consideration

The Research Ethics Committee of the Department of Agricultural Statistics at Sher-e-Bangla Agricultural University, Dhaka-1207, allowed ethical discussions to conduct the present study. All participants are informed about the purpose of the study, and the unanimity of their identity is insured, and consent from all is obtained.

Variables and measures

As the main response variable, the main concern of this study was the state of depression status and anxiety status among participants, and the two most popular methods, the Patient Health Questionnaire (PHQ-9) and Generalized Anxiety Disorder Assessment (GAD-7), were used to measure depressive symptoms and anxiety symptoms, respectively.

Patient Health Questionnaire

The Patient Health Questionnaire (PHQ-9) was used to screen the presence of depression through nine self-administered questionnaires, and every item of this questionnaire is rated on a 4-point Likert scale ranging from 0 (not at all) to 3 (nearly every day) queries the existence and rate of repetition of depressive manifestation experienced by the respondent in the last 14 days.[26,27] The total score of PHQ-9 ranges from 0 to 27, and the recommended severity cut-off scores are: None (<5), mild (5–9), moderate (10–14), moderately severe (15–19), and severe (>19). The internal consistency of this scale was very high in the present study (Cronbach coefficient Alpha = 0.813).

Generalized Anxiety Disorder Assessment

In epidemiological surveys, GAD-7 was a more valid and reliable tool, which was a questionnaire consisting of 7 items and all of them carried a point based on a four-point Likert scale ranging from 0 (not at all) to 3 (Nearly every day).[28,29] It is used to screen anxiety level and assesses its severity. According to scores of 0–4, 5–9, 10–14, and 15–21, anxiety levels are divided into four categories: Mild, mild, moderate, and severe. In the present study, Cronbach's alpha was 0.878.

Independent variables

As independent variables, we used a set of socioeconomic and demographic factors, and all of them related to depressive symptoms were considered covariates. The factors are listed below.

1. Gender (male, female)
2. Current age (<20, 21–25, >25)
3. Current living status (with family, without family)
4. Occupation status (student, job holder, unemployed)
5. Educational year (1st/2nd, 3rd/4th/5th and graduate)
6. Family status (higher class, middle class, lower class)
7. Marital status (married, unmarried)
8. Cumulative grade point average (CGPA) (≤3.00, 3.01–3.50, >3.50).

Statistical analysis

The relationship between explanatory variables and depression status was tested in a bivariate setting. In the bivariate setting, we applied the Chi-square independence test. Mathematically, the Chi-square statistic can be defined as follows:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}; i = 1, \ldots, n$$

where O_i and E_i are the observed and expected frequency, respectively. Statistics follow the Chi-square distribution with the degrees of freedom ([number of row – 1] × [number of column – 1]).

Machine learning algorithms

We used six different supervised algorithms to predict the level of depression and anxiety among university students.

Logistic regression

LR was a "statistical learning" technique, which is a "supervised" ML method specifically used for "classification" tasks. It uses the maximum likelihood estimation procedure to estimate the parameters of interest. Let $X_{i1}, X_{i2} \ldots X_{ip}$ be a set of explanatory variables, which can be quantitative variables or index variables that refer to the level of categorical variables, and Y is a binary variable, which has a Bernoulli distribution of a parameter πi, then the logit regression model is,

$$\log\left[\frac{\pi_i}{1-\pi_i}\right] = \beta_0 + \beta_1 X_{i1} + \ldots + \beta_p X_{ip}; \beta_i \text{ be the parameters.}$$

Random forest

RF is an ensemble learning-based classification approach with a large number of decision trees constructed in the training process, where the final output integrates the outcome class of individual decision trees.[30]

Support vector machine

SVM is one of the most popular classification algorithms; it has a good method of transforming nonlinear data. Chen Junli and Jiao Licheng explained the classification strategy of SVM well.[31] The linear SVM model is used in the prediction research of this mental health disease.

Linear discrimination analysis

LDA is a supervised ML technique used to extract important highlights from a data set. When these classes are well separated, the parameter estimation of the LR model is unstable. In this case, LDA is used.

K-nearest neighbors

The KNN algorithm is also the simplest and one of the most widely used classification algorithms. The KNN algorithm has confirmed the multiclass label classification problem and has good generalization ability.[32] The algorithm stores each accessible case and classifies new cases based on similarity measures.

Naive Bayes

The NB classifier is a probabilistic classifier based on the assumption of strong (naive) independence between the features of Bayes' theorem. The NB model is easy to construct without estimating complex repeat parameters, which makes it particularly effective in the treatment field. Although simple, NB classifiers usually perform well and are widely used because they outperform more complex classification methods.[33]

Proposed approach

First, apply data preparation methods, for example, distinguish missing values from the data set and process them. Subsequently, 75% of the individual samples in each group (called the training data set) were used to apply the ML algorithm, and the remaining 25% of the individuals (called the test data set) were verified. All models were trained to support 10-fold cross-validation. We used a 10-fold cross-validation in the training set and evaluated the performance in the test set.

Model evaluation

Six evaluation parameters were taken into account, named accuracy, sensitivity, specificity, positive predictive value, negative predictive value, Cohen's kappa. All data analyzes were completed using the Statistical Package for Social Sciences (SPSS) version 25 (IBM Corporation, Armonk, New York, NY, USA) and the R- programming (version 4.0.0, R Core Team).

Results

Socio-demographic characteristics of university students

Table 1 lists basic demographic and psychological characteristics, such as gender, age, residence, occupation, years of education, family status, marital status, and CGPA. In this study, slightly above half of the respondents (55%) were female, and more than one-third (77%) belonged to the 21–25 years of age group. Most of the respondents live with their families, and the percentage distribution was 86.8%. The majority (approximately, 87%) of the interviewees were undergraduate students, while the rest were unemployed or employed. Nearly half of the respondents (45%) were students and studied in the 3rd year or above. Approximately two-thirds of the respondents (67%) were from household with average income (middle-income families). Almost 43% of the respondents had an average GPA between 3.01 and 3.50.

Responses to the PHQ-9 and generalized anxiety disorder-7 questionnaire

This section describes the response rates of 9 questions on the Patient Health Questionnaire and 7 questions on the General Anxiety Disorder Questionnaire. Both questionnaires are scored on a 4-point Likert scale, ranging from 0 (not at all) to 3 (almost every day). The answers are shown in Figure 1.

Association with depression and anxiety among university students

The prevalence of severe depression and severe anxiety with the background characteristics of the selected covariate is shown in Tables 2 and 3, respectively.

In terms of depression level, the percentage of severely depressed students was higher, 37.1% of female students, 34.1% of respondents under the age of twenty, 27.4% of respondents living with their families, unemployed respondents (41.6%), respondents from poor families (37.2%), 1st/2nd year students (34.0%), unmarried respondents (28.0%), students in grades 3.01–3.50 (31.6%). It was found that all these selected covariates were significantly related to the depressive symptoms of university students ($P < 0.001$).

Table 1: Percentage distribution of university students to selected sociodemographic characteristics in Bangladesh

Covariates	Frequency (*n*=2121), *n* (%)
Gender	
Male	952 (44.9)
Female	1169 (55.1)
Age (years)	
<20	276 (13.0)
21-25	1630 (76.9)
>25	215 (10.1)
Residence	
With family	1841 (86.8)
Without family	280 (13.2)
Occupation	
Student	1843 (86.9)
Job holder	141 (6.6)
Unemployed	137 (6.5)
Educational year	
1st/2nd	849 (40.0)
3rd/4th/5th	947 (44.6)
Graduate	325 (15.3)
Family status	
Higher class	508 (24.0)
Middle class	1414 (66.7)
Lower class	199 (9.4)
Marital status	
Married	281 (13.2)
Unmarried	1840 (86.8)
CGPA (4.00 Scale)	
≤3.00	448 (21.1)
3.01-3.50	920 (43.4)
>3.50	753 (35.5)
Depression status	
Nonsevere	1554 (73.3)
Severe	567 (26.7)
Anxiety status	
Nonsevere	1654 (78.0)
Severe	467 (22.0)

CGPA: Cumulative grade point average

Table 3 shows specifying the association between the socioeconomic and demographic characteristics and anxiety status among university students in Bangladesh. According to Table 3, it was found that the relationship involving the student's gender and their anxiety status was profoundly noteworthy ($P < 0.001$). The most noteworthy rate of severe anxiety was found in female

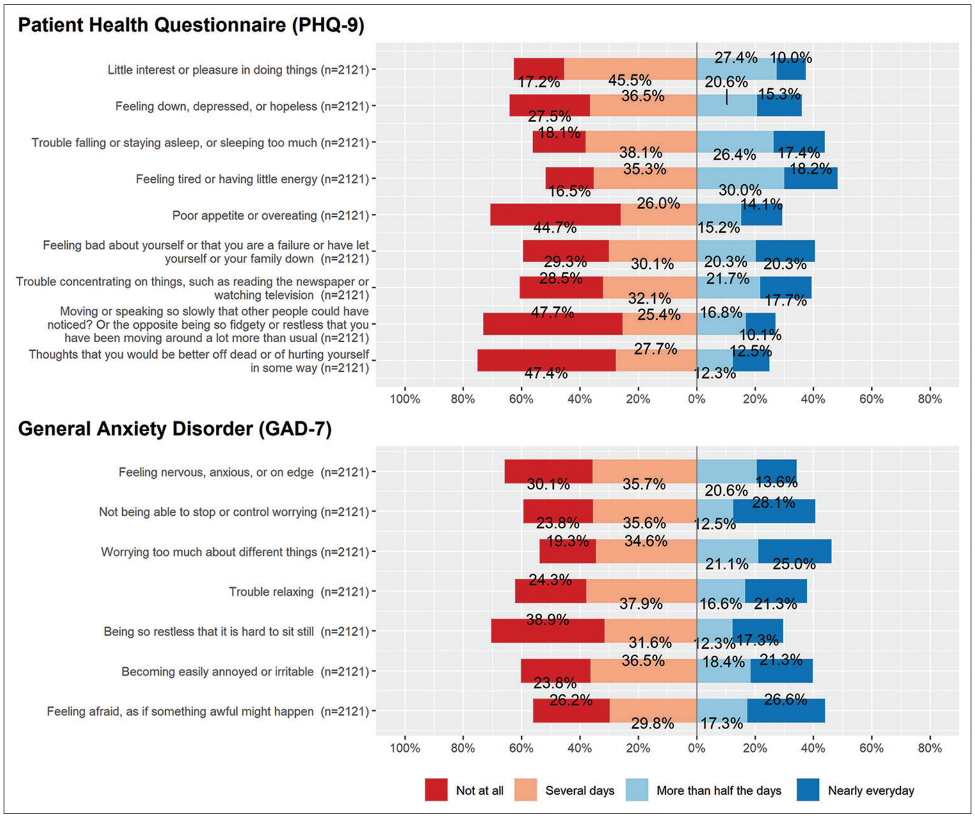

Figure 1: Percentage responses of PHQ-9 and GAD-7. GAD-7: Generalized anxiety disorder-7

students (26.1%). There was also a significant connection between the age of the students (in years) and their anxiety status (P = 0.03). Students aged more than 25 years had severe anxiety (31.2%). Students who were currently studying (22.9%) and 1st-year/2nd-year students (29.8%) had severe anxiety. It has also shown in Table 3 that an association between CGPA and anxiety status also exist (P < 0.001) and around 30% student with lower average result had severe anxiety level.

Performance parameter of machine learning algorithms

In this study, six different ML algorithms were used to classify the levels of depression and anxiety among university students in the test data set as severe and nonsevere. The predictive performance of these algorithms will be compared based on performance parameters such as accuracy, sensitivity, and specificity. In addition, Cohen's k statistic was used to determine the discrimination accuracy of the algorithm. Tables 4 and 5, respectively show the prediction results of depression and anxiety states with performance parameters for each ML algorithm (for training and testing data sets).

The performance indicators used to predict depression are shown in Table 4. Using linear discriminant analysis, the accuracy in the test data set was 74.29%, the sensitivity was 22.69%, and the specificity was 93.04%. SVM (linear) showed 74.10% accuracy, 19.14% sensitivity, and 94.07% specificity in predicting the depression status of the experimental observation results. The accuracy, sensitivity, and specificity of LR were reported as 74.48%, 22.69%, and 93.29%, respectively. However, the performance shown by the k-nearest neighborhood algorithm was 88.28%, 66.67%, and 96.13%, accuracy, sensitivity and specificity, respectively. Naive Bayes showed an accuracy of 68.24%, a sensitivity of 25.53%, and a specificity of 83.76% in predicting the depression state of the test observation results. Among the six classifiers, the best result was achieved by the RF algorithm, which showed that accuracy was 88.66%, the sensitivity was 68.79%, and specificity was 95.88%.

The Cohen kappa statistics of linear discriminant analysis, SVM (linear), naive Bayes, and LR were 0.1931, 0.1664, 0.1027, and 0.1968, respectively. It was recommended to adopt a "slightly fair agreement." However, among all executed ML algorithms, the RF algorithm showed the greatest discriminative ability (Cohen's kappa = 0.6903).

Table 5 (performance indicators for predicting anxiety states) shows that using linear discriminant analysis, the accuracy of the test data set was 79.58%, the sensitivity was 14.87%, and the specificity was 98.75%. RF showed an accuracy of 91.30%, a sensitivity of 70.25% and a specificity of 97.55% in the prediction of anxiety level in the test results. The accuracy, sensitivity, and specificity of the LR classifier were reported as 78.07%, 14.87%, and 96.81%, respectively. However, the k-nearest neighbor

Table 2: Assessing association between selected covariates and depression status among university student in Bangladesh using Chi-square test

Covariates	Depression level using PHQ-9 method	
	Severe depression (%)	Nonsevere depression (%)
Gender		
Male	14.0	86.0
Female	37.1	62.9
P	<0.001	
Age (years)		
<20	34.1	65.9
21-25	24.8	75.2
>25	32.1	67.9
P	0.01	
Residence		
With family	27.4	72.6
Without family	22.1	77.9
P	0.03	
Occupation		
Student	25.8	74.2
Job holder	24.8	75.2
Unemployed	41.6	58.4
P	<0.001	
Educational year		
1st/2nd	34.0	66.0
3rd/4th/5th	19.6	80.4
Graduate	28.3	71.7
P	<0.001	
Family status		
Rich	17.7	82.3
Middle	28.5	71.5
Poor	37.2	62.8
P	<0.001	
Marital status		
Married	18.1	81.9
Unmarried	28.0	72.0
P	<0.001	
CGPA (4.00 Scale)		
≤3.00	22.3	77.7
3.01-3.50	31.6	68.4
>3.50	23.4	76.6
P	<0.001	

CGPA: Cumulative grade point average, PHQ-9: Patient health questionnaire

Table 3: Assessing the association between selected covariates and anxiety status among university students in Bangladesh using the Chi-square test

Covariates	Anxiety level using GAD-7 method	
	Severe anxiety (%)	Nonsevere anxiety (%)
Gender		
Male	17.0	83.0
Female	26.1	73.9
P	<0.001	
Age (years)		
<20	21.7	78.3
21-25	20.9	79.1
>25	31.2	68.8
P	0.03	
Residence		
With family	22.0	78.0
Without family	22.1	77.9
P	0.51	
Occupation		
Student	22.9	77.1
Job holder	17.0	83.0
Unemployed	15.3	84.7
P	0.04	
Educational year		
1st/2nd	29.8	70.2
3rd/4th/5th	15.5	84.5
Graduate	20.6	79.4
P	<0.001	
Family status		
Rich	16.1	83.9
Middle	24.1	75.9
Poor	22.1	77.9
P	0.01	
Marital status		
Married	23.1	76.9
Unmarried	21.8	78.2
P	0.34	
CGPA (4.00 Scale)		
≤3.00	29.9	70.1
3.01-3.50	21.2	78.8
>3.50	18.3	81.7
P	<0.001	

GAD-7: Generalized Anxiety Disorder Assessment, CGPA: Cumulative grade point average

algorithm showed the same performance as the RF, with accuracy, sensitivity, and specificity of 91.30%, 73.55%, and 96.57%, respectively. Naive Bayes showed an accuracy of 73.53%, a sensitivity of 24.13%, and a specificity of 94.11% when predicting the anxiety state of the test respondents.

Among these six classifiers, the best result was achieved by the SVM (linear) algorithm, showing that the accuracy was 91.49%, the sensitivity was 67.77%, and the specificity was 98.53%. According to Cohen's kappa value of SVM classifier, the data showed that the reliability exceeded 60% (k = 0.7333).

This violin plot shows the relationship of seven classifiers to accuracy. The shaded areas detail the distribution of the data in each classifier. In terms of depression, Figure 2a shows that RF provided the highest mean accuracy, followed by KNN, LR, LDA, SVM, and NB. Figure 2b shows that SVM provided the highest mean accuracy for anxiety, followed by RF, KNN, LDA, LR, and NB. Unlike the boxplot, the entire distribution

Table 4: Performance indicators of all five machine learning algorithms to predict depression status

	Algorithms					
	LR	RF	SVM	LDA	KNN	NB
Training set						
Accuracy (%)	75.63	89.76	74.62	75.31	89.38	70.79
95% CI	73.44-77.72	88.17-91.21	72.41-76.75	73.12-77.42	87.77-90.86	68.49-73.02
κ	0.2537	0.7220	0.1835	0.2474	0.7099	0.1504
Sensitivity (%)	28.17	71.36	19.95	28.17	69.72	26.06
Specificity (%)	92.97	96.48	94.60	92.54	96.57	87.14
PPV	59.40	88.12	57.43	57.97	88.13	42.52
NPV	77.98	90.22	76.38	77.90	89.72	76.33
Test set						
Accuracy (%)	74.48	88.66	74.1	74.29	88.28	68.24
95% CI	70.54-78.14	85.64-91.23	70.15-77.79	70.34-77.97	85.23-90.9	64.09-72.19
κ	0.1968	0.6903	0.1664	0.1931	0.6769	0.1027
Sensitivity (%)	22.69	68.79	19.14	22.69	66.67	25.53
Specificity (%)	93.29	95.88	94.07	93.04	96.13	83.76
PPV	55.17	85.84	54.00	54.23	86.24	36.36
NPV	76.85	89.42	76.20	76.80	88.81	75.58

LR: Logistic regression, RF: Random forest, SVM: Support vector machine, LDA: Linear discriminant analysis, KNN: K-nearest neighborhood, NB: Naïve Bayes, PPV: Positive predictive value, NPV: Negative predictive value, CI: Confidence interval

Table 5: Performance indicators of the five machine learning algorithms to predict anxiety status

	Algorithms					
	LR	RF	SVM	LDA	KNN	NB
Training set						
Accuracy (%)	80.78	93.09	92.27	81.78	92.9	76.26
95% CI	78.76-82.69	91.73-94.29	90.85-93.54	79.8-83.65	91.53-94.11	74.09-78.33
κ	0.2565	0.7852	0.7525	0.2775	0.7834	0.1448
Sensitivity (%)	22.54	76.59	70.81	22.25	78.61	28.09
Specificity (%)	96.95	97.67	98.23	98.31	96.87	95.18
PPV	67.24	90.14	91.76	78.57	87.46	31.81
NPV	81.84	93.76	92.38	81.99	94.22	78.85
Test set						
Accuracy	78.07	91.3	91.49	79.58	91.3	73.53
95% CI	74.3-81.53	88.57-93.56	88.78-93.73	75.89-82.94	88.57-93.56	69.56-77.25
κ	0.1583	0.7334	0.7333	0.1909	0.7399	0.1827
Sensitivity (%)	14.87	70.25	67.77	14.87	73.55	24.13
Specificity (%)	96.81	97.55	98.53	98.77	96.57	94.11
PPV	58.06	89.47	93.18	78.26	86.41	17.24
NPV	79.31	91.71	91.16	79.64	92.49	76.80

CI: Confidence interval, LR: Logistic regression, RF: Random forest, SVM: Support vector machine, LDA: Linear discriminate analysis, KNN: K-nearest neighbors, NB: Naïve Bayes, PPV: Positive predictive value, NPV: Negative predictive value

of the 10-fold accuracy can be visualized in this violin plot [Figure 2].

Discussion

To the best of our knowledge, this is the first study to apply several machine classifiers to predict the level of depression and anxiety status among university students during the first wave of COVID-19 in Bangladesh.

In Bangladesh, mental health illnesses were not as important as all other public health issues such as malnutrition, and mental health issues are now becoming a major issue around the world.[34] Few studies have been conducted on mental disorders among college students.[35,36] Thus, the main focus of the study was to predict the state of mental disorders such as depression and anxiety among Bangladeshi university students. To fulfill our study objective, this study used six well-known ML algorithms. All models were trained based on 10-fold cross-validation on the training set, and performance was estimated in the testing set.

The prevalence of severe depression and severe anxiety was higher for female than for male. A recent systematic

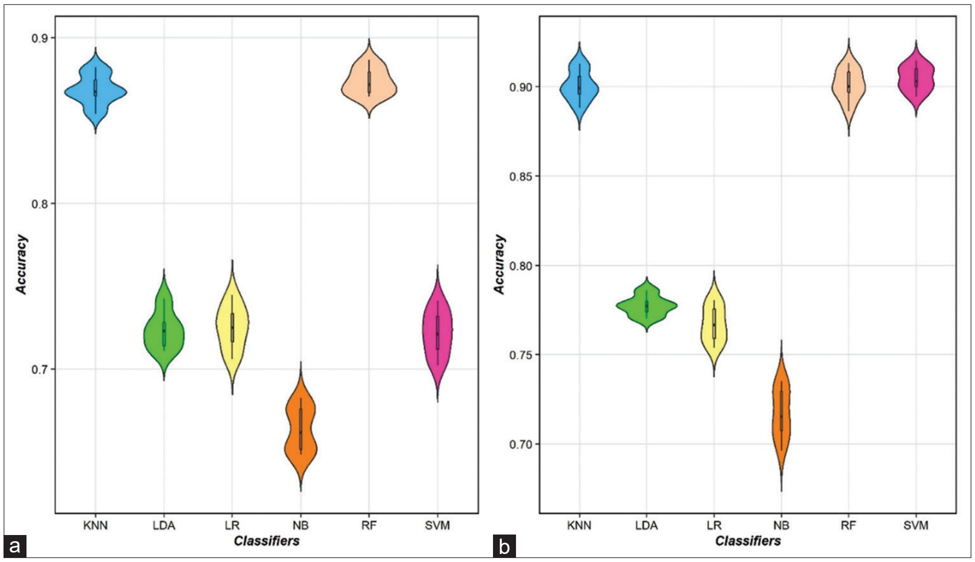

Figure 2: Violin plot showing depression accuracy (a) and anxiety accuracy (b) in each machine learning classifiers

review analysis depicts that female gender was significantly important to increase the depression symptom.[37] This study found a high prevalence of depression and anxiety problem for teenage students who were currently in the study. There are many psychological reasons for higher percentage of severe mental health problem among students. For instances, students felt insecure about their future career during this pandemic situation.[5] Lower academic performance is also an important and significant indicator for increasing the mental health problem among university students.[38]

From supervised model comparison, the best accuracy was achieved by the RF algorithm for depressed sectors based on various performance parameters. But for anxiety states, the SVM showed the best predictive estimate with 91% accuracy. Compared to previous research SVMs, it performed with a reasonable level of accuracy among all classifiers.[39] In other areas of public health, such as malnutrition and anemia in children, the RF has great predictive potential.[40,41] In research related to mental health or medical sector, RF and support vector algorithm were used mostly to predict psychiatric disorder and disease outcome, respectively, by several researchers.[42-46] Finally, this study proposed that the classification of RFs and vector machines be extended where Bangladesh's coerced concern is predicting mental health problems, for example, depression and anxiety.

Limitations

Almost all studies will have few impediments, and current research is not without limitations that must be taken seriously during data interpretation. First, the nature of this research is cross-sectional, for which it is quite impossible to provide a causal relationship. During the lockdown, data collection is really impossible, for that reason, we have conducted the online structure questionnaire method. Second, the study was conducted by interviewing online with a small number of students from four universities, not representing university students from the whole country. Finally, due to the online survey, few students were unable to complete the questionnaire by their own hands and provide accurate information due to mental shame.

However, this investigation established that ML algorithms can be used to predict psychological state malady supported common risk factors, which can assist within the development of interventions to prevent severe psychological state issues among students, particularly university students in Bangladesh.

Conclusions

This study focuses mainly on the comparison of the performance of ML-based algorithms to predict depression and anxiety among university students during the first wave of the COVID-19 pandemic in Bangladesh. This research is also important for policymakers since Bangladesh has the second-highest temporary university closed in the world in an attempt to contain the spread of the COVID-19 pandemic. During the time of the first wave of the COVID-19 pandemic, students faced severe mental health problems. Based on the study findings, the prevalence of severe depression and severe anxiety among university students was 26.7% and 22%, respectively. In summary, we conclude that among ML classifiers, a RF is best for predicting depression, and an SVM is best for predicting anxiety. Finally, we suggest that RF and SVMs are the core interests of researchers in predicting depression and anxiety among university students, respectively.

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Declaration of respondent consent

The authors certify that they have obtained all appropriate university student consent.

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Conflicts of interest

There are no conflicts of interest.

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