A Machine Learning Approach to Assess Psychological State Among University Students Throughout the Covid-19 Pandemic: Bangladesh Perspective

‘

Anower Hossen
Computer Science & Engineering
International Islamic University Chittagong
Chattogram, Bangladesh
a.h.sumon2607@gmail.com

Rahim Uddin Rafin
Computer Science & Engineering
International Islamic University Chittagong
Chattogram, Bangladesh
rafinc10@gmail.com

Mahin Mahtab
Computer Science & Engineering
International Islamic University Chittagong
Chattogram, Bangladesh
mahin.mahtab.1@gmail.com

Shahidul Islam Khan
Computer Science & Enginneering
International Islamic University Chittagong
Chattogram, Bangladesh
nayeemkh@gmail.com

***Abstract* - The COVID-19 outbreak in Bangladesh had a negative impact on people of all ages. The epidemic's destruction clearly had an effect on people's mental health, especially that of university students. From the beginning of the pandemic in Bangladesh, educational institutes were shut down, complete lockdown condition, unable to get sports and entertainment abilities, which caused the student's psychological health to suffer. Most university-aged students exhibited long-lasting psychological issues corresponding with COVID-19, including significant levels of stress, anxiety, and depression. Predicting the psychological state will indicate a lack of psychological resilience, which will be associated with mental health problems among Bangladeshi university students. Increasing psychological fortitude is essential to ensuring pupils' well-being throughout the epidemic. Through an online survey and several machine learning algorithms, our system predicts the psychological state of Bangladeshi university students. We preprocessed this dataset by cleaning it correctly for the procedure. We utilized hyper-parameter tweaking to extract the features, and then we trained the dataset using a number of classifiers, such as the support vector classifier, random forest, logistic regression, decision tree, naive Bayes, KNN, and gradient boosting. Study suggests that, these algorithms works best in researching on mental health related datasets. Among these several machine learning algorithms, our created dataset of 509 points, comprising support vector classifier (SVC), produced an AUROC score of 0.98, 0.97, and 0.97 for depression, anxiety, and stress states, respectively. Additionally, SVC also delivered respectable outcomes on the open-source dataset we collected for each of the psychological states - depression, anxiety, and stress. Support vector machine (SVM), a supervised machine learning model that employs classification methods, may, in general, produce excellent results when there is a distinct proportion of displacement between classes. By evaluating a dataset we have collected and enhancing the DASS-21 formulation to measure an individual's depression, anxiety, and stress. DAAS-21 is well established screening method for addressing mental health issue. We sincerely considered the ethics and all the data we collected from people are preserved with care and utmost privacy. This study will aid in the growth of research into the area of suicidal thoughts and emotional states.**

Keywords: SVC, KNN, GB, DT, Random Forest, Logistic Regression, DASS-21, Depression, Stress, Anxiety, Hyper-parameter Tuning

I. INTRODUCTION

University students have experienced greater levels of worry, psychological stress, and sadness as a result of the pandemic's effects on people's mental health [3]. A sufficient number of studies that take into account the main components of a psychological state, such as stress, anxiety, and depression, have not yet been discovered, according to the Bangladeshi viewpoint, since the majority of Bangladeshi publications and papers focus on physical rather than psychological difficulties, such as pulse rate, systolic and diastolic blood pressure, or depression levels. Due to a lack of study, it is still unclear how the pandemics have affected the students, even though the DASS-21 questionnaire covers all psychological states, including stress, anxiety, and depression [4]. Additionally, it is crucial to determine whether the pupils were sad, nervous, or agitated at the time and the reasons for these feelings.

In [9] researchers worked on university students mental health using three conventional ML algorithm. And they usd an open source dataset containing 219 data.

Paper [10] authors used online questuinnaire survey to collect 651 data from adult Bangladshis. They developed a series of techniques like T-test, principal component analysis (PCA), hierarchical cluster analysis (HCA),and Pearson's correlation matrix (PCM) to determine the connection between various components and significant causes that led to adult mental stress.

In [11] researcher predicted depression in job sectors in Bangladesh and used variety of classifiers to identify the componentthat contributed most to depression.

In [12] a perception based study was done. By conducting online poll they collected data nad sleep deprivation, irritability and familiy conflict were among the findings of this paper.

In [13] researcher investigated how well young Chinese students evolved psychologically during the Covid19 pandemic using symptms of anxiety and insomnia with XG Boost algorithm showing 97.3% accuracy.

In [15] authors collected data through questionnaire and compared performance of different ML algorithms.

In [19] researchers predicted anxiety, depression and stress. After collecting data in DASS-21 questionnaire method they used five clasifier to predict stress, anxiety and depression.

In the present COVID-19 pandemic, people's psychological states have become a major battleground, and the prevalence of worry, stress, and despair has increased during the epidemic. As a result, the goal of our study is to compile the available data on the prevalence of mental health status throughout the pandemic and lay the groundwork for mental health education. The study's goals are as follows:

- To employ machine learning algorithms for predicting mental health based on standard DASS-21 questionnaires.
- To examine the students' mental health during the epidemic in order to comprehend its causes and responses.
- To determine the most reliable algorithms and crucial psychological variables that reflect student's mental health.

II. METHODOLOGY

A. *Data Collection*

For the purpose of refining our system, we generated a dataset comprising 509 data points. We designed a Google Form with a set of questions as an online questionnaire survey that we gave to university students to get input on their psychological health in the areas of stress, anxiety, and depression in addition to creating our dataset. And we maintained privacy of the data we collected. Additionally, we collected a public dataset of 971 data samples named DASS-21 [20].

B. *Data Preprocessing*

Several students ought to receive assistance to complete the form, and some left off some questions, making it challenging to find the missing data. The missing data would hamper the next step. For this reason, we preprocessed our dataset to eliminate null values from the comma-separated values (CSV) file, and we subsequently obtained a flawless dataset with all the data.

C. *Feature Engineering*

In this study, we attempted to extract stress, anxiety, and depression characteristics from the available data. We have to use the method described in [4] to measure the emotional states of stress, anxiety, and depression from self-report scales. The three DASS-21 scales—depression, anxiety, and stress—each has seven entities broken down into subscales with relevant threads. The process for calculating depression, anxiety, and stress is shown in the equations below.

$$Depression, \sum All\ the\ entities\ \times 2\ \leq 9 \qquad (2.1)$$

$$Anxiety, \sum All\ the\ entities\ \times 2\ \leq 7 \qquad (2.2)$$

$$Stress, \sum All\ the\ entities\ \times 2\ \leq 14 \qquad (2.3)$$

If all of these entity values are summed together, the result must be less than half of nine when determining whether a person is depressed. The number nine is changed to seven for anxiety and fourteen for stress.

Through the use of only key data and the elimination of redundant information, we have reduced the input variable for the model using the feature selection technique.

We collected data on age, gender, educational level, living area, marital status, family type, and whether or not they were infected with the coronavirus, as well as the 21 (7 for depression, anxiety, and stress) essential data defined by DASS21 [4] for the prediction. According to the correlation matrices in Fig. 2.1, the 7 relevant data points that are related to the depression state appear to have significant impacts on a person's prediction of depression

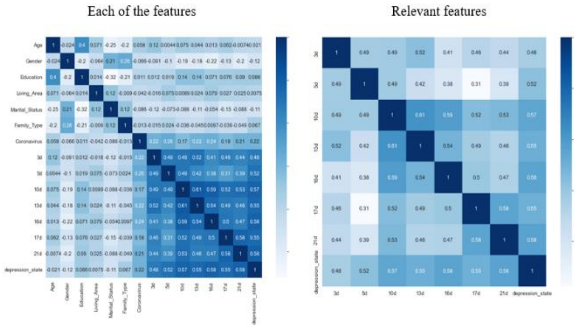

Fig. 2.1: Correlation matrices for depression state

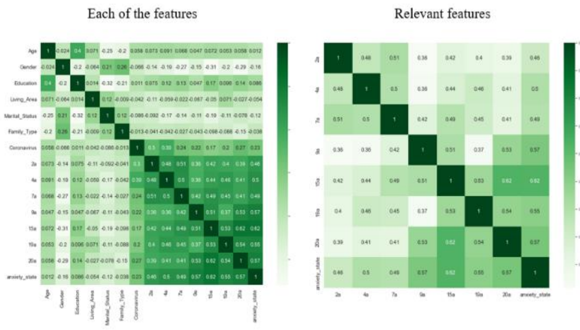

Fig. 2.2: Correlation Matrices for Anxiety state

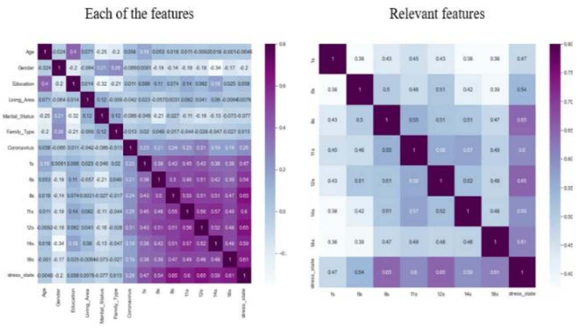

Fig. 2.3: Correlation matrices for stress state

Figures 2.2 and 2.3 demonstrate how the 7 relevant features, rather than all the features, influence the prediction of anxiety and stress. Therefore, we have preferred 7 features in each of the three areas of stress, anxiety, and depression.

D. *Model Training*

The complete dataset was split into 80% and 20% of the processed data, respectively. Selecting the best collection of hyper-parameters for a learning algorithm is known as "hyper-parameter tuning" [22]. A model input called a hyper-parameter has its value predetermined before the learning process even starts. Hyper-parameters cannot be directly learned from the data because they are not model parameters. Model parameters are discovered during training when we use a technique like a gradient descent to optimize a loss function [23]. The hyper-parameters provide the actual structure of our model, while the model parameters specify how to translate the input data into the desired output. Hyper-parameters are tweaked to give the best fit after learning model parameters from the data. Because finding the optimum hyper-parameter might be time-consuming, grid search and random search are utilized in the search process. Also, we checked if our dataset is overfitting by fitting our dataset into oversampling and under sampling technique and found that the dataset gives similar output in both ways. And also, compared the results to another dataset but found the result to be correct.

TABLE I. BEST PARAMETERS FOR EACH OF THE ALGORITHMS FOR ALL THERE (DEPRESSION, ANXIETY AND STRESS) STATES

Algorithms	**Depression**	**Anxiety**	**Stress**
SVC	{'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}	{'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}	{'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}
Logistic Regression	{'C': 1}	{'C': 1}	{'C': 10}
Random Forest	{'n_estimators': 10}	{'n_estimators': 10}	{'n_estimators': 10}
K-Nearest Neighbors	{}	{}	{}
Multinomial Naïve Bayes	{}	{}	{}
Decision Tree	{'criterion': 'entropy'}	{'criterion': 'gini'}	{'criterion': 'gini'}
Gradient Boosting	{'learning_rate': 0.001, 'n_estimators': 10}	{'learning_rate': 0.001, 'n_estimators': 10}	{'learning_rate': 0.01, 'n_estimators': 30}

Hyper-parameter optimization was used to find the ideal set of parameters and control how our algorithms learn. Models were trained with various parameters and looped as a cross-validation fold of 5 after splitting the data to achieve the most reliable performance. Table 1 lists all parameters with the optimal values for each algorithm for all there (depression, anxiety and stress) states.

E. PERFORMANCE EVALUATION

Performance evaluation measures determine the performance of the machine learning models that we have recruited. Comparing the model's predictions with the (known) values of the dependent variable in a dataset forms the basis of most model-performance metrics. Out of the several performance evaluation matrices available, we utilized the most commonly used performance measures, including the confusion matrix, accuracy, precision, recall, f1-score, and ROC curve. It forecasts the evaluation report's matrix using data from true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

F. ACCURACY

Accuracy calculated as the observed value divided by the actual value, expressed as a percentage.

$$Accuracy = \frac{TP + FN}{TP + TN + FP + FN} \tag{2.4}$$

G. PRECISSION

Precision is calculated as the sum of all correctly predicted positive observations divided by all correctly predicted positive statements.

$$Precision = \frac{True\ Positives}{True\ Positives \times False\ Positives} \tag{2.5}$$

H. RECALL

The proportion of accurately anticipated positive observations to all actual positive statements in the class is known as "recall."

$$Recall = \frac{True\ Positives}{True\ Positives \times False\ Negative} \tag{2.6}$$

I. F1- SCORE

The f1-score is a weighted average of recall and accuracy.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{2.7}$$

J. ROC CURVE

The evaluation method, known as the "receiver operating characteristic (ROC) curve," analyzes sensitivity vs. specificity across a range of values to predict a binary occurrence. The true positive rate (sensitivity) for a classification model at various thresholds is calculated and plotted against the false positive rate (specificity) to form the ROC curve.

$$True\ Positive\ Rate = \frac{True\ Positives}{True\ Positives + False\ Negative} \tag{2.8}$$

$$False\ Positive\ Rate = \frac{False\ Positives}{False\ Positives + True\ Negative} \tag{2.9}$$

III. RESULTS AND DISCUSSIONS

A. Experimental Analysis

Experimental analysis is a quantified statement of the values that are used to fulfill the objectives. To assess the performance of our developed methodology, we utilized a variety of performance metrics. The confusion matrix, precision, recall, f1-score and ROC curve have all been described for the experimental analysis of our system. These documents explain how our system was created and whether it is successful or not.

B. Confusion Matrix

. The confusion matrix of the SVC for depression, anxiety, and stress is shown sequentially in Figures 3.1, 3.2 and 3.3 below.

.

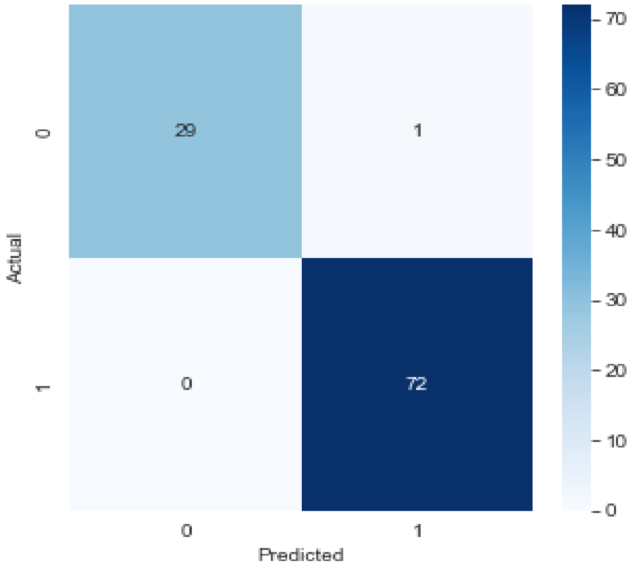

Fig. 3.1: Confusion Matrix for SVC(depression state)

We have demonstrated the SVC's confusion matrix because it outperformed the other algorithms in terms of outcomes. The confusion matrix for the depressive state is shown in Fig. 3.1. This image's 0–1 diagonal parts are true positive, meaning that these values are expected to be true as they are. The SVC was able to correctly predict 101 data samples for the test set of 102 data samples, with 29 being predicted as not depressed (0) and 72 being predicted as depressed (1). Only 1 data sample from class 0 had an incorrectly predicted value of 1

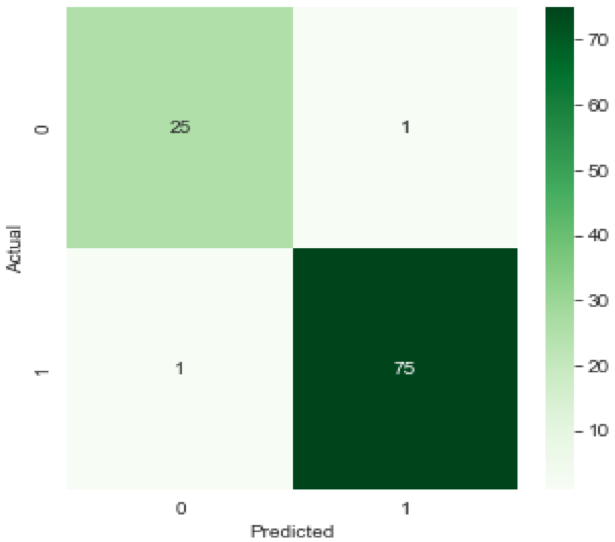

Fig. 3.2: Confusion matrix for SVC(anxiety state)

As illustrated by Fig. 3.2, the SVC was able to accurately forecast 100 data samples for the test set of 102 data samples for anxiety state, 75 were predicted to have anxiety (1), while 25 were predicted to have no anxiety (0). Only two from class 0 and class 1 data sample were predicted inaccurately.

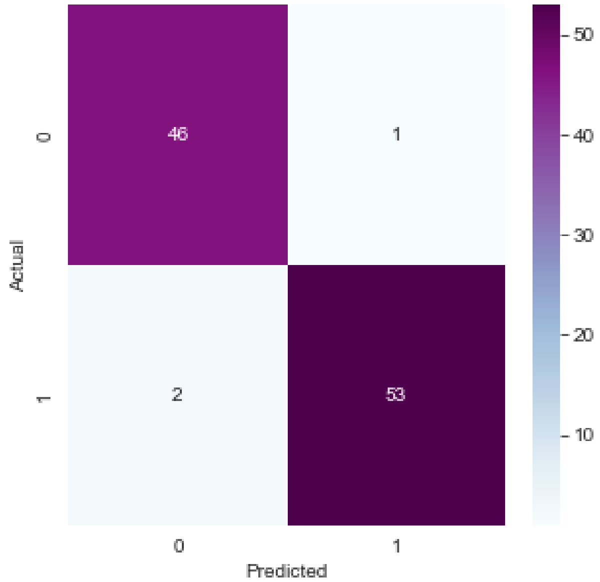

Fig. 3.3: Confusion matrix for SVC(stress)

Similar to depression and anxiety, the SVC was able to accurately predict 99 data samples for the test set of 102 data samples for stress state. As shown in Fig. 3.3, only one data point from the no stress class was projected as stress, with 46 being predicted as not stress (0) and 53 being projected as stress (1). Only one from class 0 and two from class 1 data sample were predicted inaccurately

C. *Classification Report*

The SVC's classification report for depression, anxiety, and stress is displayed in Table II, III, and IV respectively.

TABLE II. CLASSIFICATION REPORT OF SVC(DEPRESSION STATE)

	precision	**recall**	**f1-score**	**support**
0	1.00	0.97	0.98	30
1	0.99	1.00	0.99	72
accuracy			0. 99	102
macro avg	0.99	0. 98	0.99	102
weighted avg	0. 99	0. 99	0.99	102

The classification report in Table II shows that the SVC classifier's values for precision, and f1-score for the depressive state were relatively were relatively similar. whereby recall achieved a 0.97 rate at class 0 and 1 at class 1.

TABLE III. CLASSIFICATION REPORT OF SVC(ANXIETY STATE)

	precision	**recall**	**f1-score**	**support**
0	1.00	0.94	0.96	26
1	0.98	1.00	0.99	76
accuracy			0.98	102
macro avg	0.97	0.97	0.97	102
weighted avg	0.98	0.98	0.98	102

The SVC classifier has an approximate precision of 0.99 for the anxiety state, as shown by the classification results in Table III, where precision, recall and f1-score were measured at 0.96 and 0.99 respectively.

TABLE IV. CLASSIFICATION REPORT OF SVC (STRESS STATE)

	precision	recall	f1-score	support
0	0.96	0.98	0.97	47
1	0.98	0.96	0.97	55
accuracy			0.97	102
macro avg	0. 97	0. 97	0.97	102
weighted avg	0. 97	0. 97	0.97	102

The classification reports in Table IV demonstrate that the SVC's precision, recall are relatively similar as 0.96 and 0.98, and f1-score values for the stress state is 0.97.

D. ROC CURVE

Figures 3.4, 3.5 and 3.6 illustrate the ROC curves of the SVC for depression, anxiety and stress.

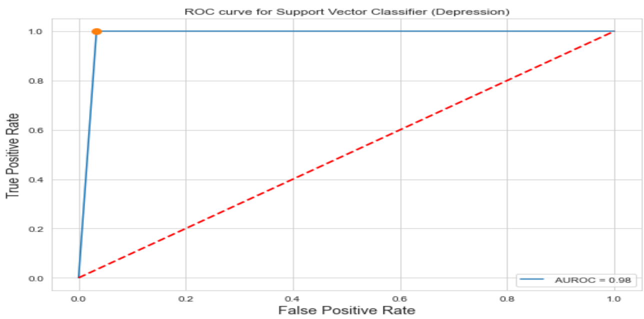

Fig. 3.4: ROC curve for SVC (depression state)

We have shown the ROC curve of the SVC since it beat the other algorithms in terms of performance. Fig. 3.4 depicts the ROC curve for the depressed state. Plotting the ROC curve for the depressed state contrasts sensitivity (TPR) against specificity (FPR), with sensitivity (TPR) on the y-axis and specificity (FPR) on the x-axis. The AUROC value is 0.98 on the ROC curve shown in Fig. 3.2, where it remains within the range of 0 and 1. When the AUROC is larger, the model is more accurate at predicting that 0 classes will be 0 and 1 class will be 1.

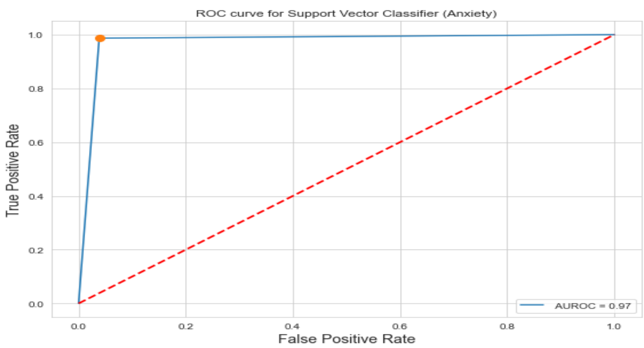

Fig. 3.5: ROC curve for SVC (anxiety)

Fig. 3.5 shows the ROC curve for the anxiety state, with an estimated AUROC value of 0.97. This indicates the precise result of SVC for the anxiety state for our dataset.

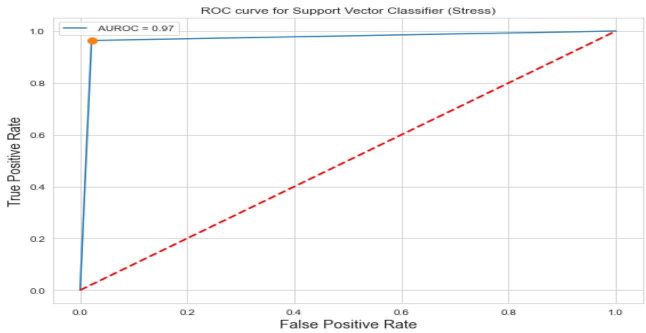

Fig. 3.6: ROC curve for SVC (stress)

The ROC curve for the stress state is displayed in Fig. 3.6, with an approximated AUROC value of 0.97.

E. Result Comparison

We used the dataset of 509 samples we generated for the evaluation of our algorithms. Additionally, we used the dataset from DASS-21 [20]. The author's analysis included a dataset of 971 samples. The following tables compares the accuracy for each of the machine learning methods we used to create our concepts

TABLE V. ACCURACY COMPARISON BETWEEN OUR DATASET AND DASS21 DATASET FOR DEPRESSION

Dataset	Algorithms	Cross Validation	precision	recall	f1-score
Our Dataset	SVC	0.978	0.99	0.99	0.99
	Random Forest	0.944	0.94	0.94	0.94
	Logistic Regression	0.961	0.98	0.98	0.98
	Multinomial Naïve Bayes	0.678	0.60	0.69	0.60
	K-Nearest Neighbors	0.973	0.97	0.97	0.97
	Gradient Boosting	0.72	0.50	0.71	0.58
	Decision Tree	0.885	0.91	0.91	0.91
DASS21	SVC	0.974	0.97	0.97	0.97
	Random Forest	0.957	0.91	0.91	0.91
	Logistic Regression	0.967	0.98	0.97	0.97
	Multinomial Naïve Bayes	0.698	0.59	0.70	0.63
	K-Nearest Neighbors	0.965	0.96	0.96	0.96
	Gradient Boosting	0.726	0.56	0.75	0.64
	Decision Tree	0.863	0.86	0.84	0.85

Table V demonstrates that SVC methods obtained the greatest accuracy for both datasets on depression state. While DASS-21's dataset [20] employed SVC to achieve a cross validation score of 0.983, our dataset was able to achieve a cross validation score of 0.978.

TABLE VI. ACCURACY COMPARISON BETWEEN OUR DATASET AND DASS21 DATASET FOR ANXIETY

Dataset	Algorithms	Cross Validation	precision	recall	f1-score
Our Dataset	SVC	0.973	0.98	0.98	0.98
	Random Forest	0.956	0.94	0.94	0.94
	Logistic Regression	0.966	0.97	0.97	0.97
	Multinomial Naïve Bayes	0.629	0.65	0.72	0.66
	K-Nearest Neighbors	0.946	0.92	0.91	0.91
	Gradient Boosting	0.656	0.56	0.74	0.64
	Decision Tree	0.889	0.86	0.86	0.86
DASS21	SVC	0.983	0.96	0.96	0.96
	Random Forest	0.959	0.98	0.97	0.97
	Logistic Regression	0.965	0.98	0.98	0.98
	Multinomial Naïve Bayes	0.76	0.75	0.81	0.77
	K-Nearest Neighbors	0.964	0.96	0.95	0.96
	Gradient Boosting	0.782	0.84	1.00	0.91
	Decision Tree	0.899	0.92	0.92	0.92

SVC algorithms yielded the highest levels of accuracy for both datasets on anxiety state, as shown in Table VI. Our dataset was able to reach a cross validation score of 0.973, while DASS-21's dataset [20] used SVC to obtain a cross validation score of 0.983.

TABLE VII. ACCURACY COMPARISON BETWEEN OUR DATASET AND DASS-21[20] STRESS STATE

Dataset	Algorithms	Cross Validation	precision	recall	f1-score
Our Dataset	SVC	0.99	0.97	0.97	0.97
	Random Forest	0.919	0.93	0.92	0.92
	Logistic Regression	0.983	0.96	0.96	0.96
	Multinomial Naïve Bayes	0.553	0.49	0.50	0.49
	K-Nearest Neighbors	0.899	0.95	0.95	0.95
	Gradient Boosting	0.899	0.89	0.89	0.89
	Decision Tree	0.868	0.79	0.79	0.79
DASS21	SVC	0.995	0.99	0.99	0.99
	Random Forest	0.948	0.96	0.96	0.96
	Logistic Regression	0.989	0.99	0.99	0.99
	Multinomial Naïve Bayes	0.646	0.63	0.64	0.61
	K-Nearest Neighbors	0.961	0.94	0.94	0.94
	Gradient Boosting	0.905	0.90	0.90	0.90
	Decision Tree	0.879	0.86	0.86	0.86

Table VII indicates that the results for the stress state appear to be very equivalent to those for the anxiety state. We were able to get a cross validation score of 0.973 with our dataset, as opposed to the DASS-21 dataset [20] using SVC to reach a cross validation score of 0.995.

F. Discussions

Our study was intended to employ machine learning algorithms for predicting mental health based on standard DASS-21 questionnaires. Hence, we have employed machine learning algorithms for predicting mental health based on standard DASS-21 questionnaires. Before implementing different machine learning algorithms in the prediction stage, we used a couple of adequate but essential steps, such as data preprocessing, feature engineering, and hyper parameter tuning. To examine the students' mental health during the epidemic in order to comprehend its causes and responses, we built this system using knowledge from previous studies and made an effort to implement our plan. By dividing this mental health issue into three categories—depression, stress, and anxiety—we got a variety of viewpoints from young people. To determine the most reliable algorithms and crucial psychological variables that reflect students' mental health, we employed several machine learning algorithms, where, an AUROC score of 0.98, 0.97, and 0.97 was obtained for depression, anxiety, and stress state, respectively, from our constructed data set of 509 points that included a support vector classifier (SVC). According to various performance matrices, SVC appears to outperform other machine learning algorithms on the gathered dataset when contrasting the outcomes of our created dataset with the best-performing algorithms.

IV. CONCLUSION

Worldwide, COVID-19 has claimed the lives of millions of individuals, and persistent health problems have plagued even those who have survived the disease [24]. Furthermore, because coronavirus is a severe issue, university students were more psychologically impacted throughout. The COVID scenario, the mental condition of individuals during the pandemic, and several serious diseases that affected people were all the subjects of extensive research because of this. Our study predicts mental states during COVID among university students in Bangladesh. We used other research to create this system and attempted to implement our strategy. We have used an online survey form to collect different opinions from youngsters and subdivided this mental issue into three categories, such as depression, stress, and anxiety; we execute this system using machine learning algorithms. Our approach aims to predict the psychological state of these three, and we gained good accuracy in these three categories. According to our study, Bangladeshi university students' mental conditions during COVID may be predicted. We built this system using knowledge from previous studies and made an effort to implement our plan. By dividing this mental health issue into three categories depression, stress, and anxiety—we got a variety of viewpoints from young people. We then utilized machine learning methods to implement this approach. Our methodology attempts to infer mental state from these three, and we found that we were relatively accurate.

A. Contribution And Future Works

The major contributions in the research are we created a dataset that is publicly accessible with a variety of variables for assessing psychological status (depression, stress, and anxiety). Secondly, we analyzed the accuracy of several machine learning algorithms in accordance with the appropriate feature engineering and found that SVC had amazing accuracy, at 99%, 98% and 97% and AUROC score of 0.98, 0.97, and 0.97 for depression, anxiety, and stress states, respectively.

Some aspects of the present research work can be further investigated and improved. Firstly, working on a vast collection of psychological features, expanding the dataset, and retraining the neuron network would be the most significant future work for this current topic. Secondly, a concurrent technique may reduce the time required for fixed and learnable algorithms. Work on more robust and relatively low-cost aesthetic systems will also continue

REFERENCES

[1] M. Nabila Ashraf *et al.*, ‘Mental Health Issues in the COVID-19 Pandemic and Responses in Bangladesh: View Point of Media. Reporting’, *Front Public Health*, vol. 9, Sep. 2021, doi: 10.3389/fpubh.2021.704726

[2] S. Far et al., ‘Socio-psychological impact on Bangladeshi students during COVID-19’, 2020.

[3] ‘Students left to suffer from Covid-linked depression’. https://www.tbsnews.net/coronavirus-chronicle/covid-19-bangladesh/students-left-suffer-covid-linked-depression-236875 (accessed Nov. 22, 2022).

[4] S. H. Lovibond and P. F. Lovibond, Manual for the depression anxiety stress scales. Psychology Foundation of Australia, 1996.

[5] COVID-19 and your mental health - Mayo Clinic’. https://www.mayoclinic.org/diseases-conditions/coronavirus/in-depth/mental-health-covid-19/art-20482731 (accessed Nov. 22, 2022).

[6] School closure longest in Bangladesh, learning vacuum alarming: Educationists’. https://www.tbsnews.net/bangladesh/education/school-closure-longest-bangladesh-learning-vacuum-alarming-educationists-372592 (accessed Nov. 22, 2022).

[7] L. Yan, A. Whitelock-Wainwright, Q. Guan, G. Wen, D. Gašević, and G. Chen, ‘Students’ experience of online learning during the COVID-19 pandemic: A province-wide survey study’, British Journal of Educational Technology, vol. 52, no. 5, pp. 2038–2057, Sep. 2021, doi: 10.1111/BJET.13102.

[8] R. M. Khalil and A. Al-Jumaily, ‘Machine learning based prediction of depression among type 2 diabetic patients’, in Proceedings of the 2017 12th International Conference on Intelligent Systems and Knowledge Engineering, ISKE 2017, Jul. 2017, vol. 2018-January, pp. 1–5. doi: 10.1109/ISKE.2017.8258766.

[9] F. Sahlan, F. Hamidi, M. Z. Misrat, M. H. Adli, S. Wani, and Y. Gulzar, ‘Prediction of Mental Health Among University Students’, 2021.

[10] S. Amit, L. Barua, and A. al Kafy, ‘A perception-based study to explore COVID-19 pandemic stress and its factors in Bangladesh’, Diabetes Metab Syndr, vol. 15, no. 4, p. 102129, Jul. 2021, doi: 10.1016/j.dsx.2021.05.002.

[11] N.N. Moon, A. Mariam, S. Sharmin, M. M. Islam, F. N. Nur, and N. Debnath, ‘Machine learning approach to predict the depression in job sectors in Bangladesh’, Current Research in Behavioral Sciences, vol. 2, Nov. 2021, doi: 10.1016/j.crbeha.2021.100058.

[12] S. M. D. U. Islam, M. Bodrud-Doza, R. M. Khan, M. A. Haque, and M. A. Mamun, ‘Exploring COVID-19 stress and its factors in Bangladesh: A perception-based study’, Heliyon, vol. 6, no. 7, Jul. 2020, doi: 10.1016/j.heliyon.2020.e04399.

[13] F. Ge, D. Zhang, L. Wu, and H. Mu, ‘Predicting psychological state among chinese undergraduate students in the covid-19 epidemic: A longitudinal study using a machine learning’, Neuropsychiatr Dis Treat, vol. 16, pp. 2111–2118, 2020, doi: 10.2147/NDT.S262004.

[14] M. M. Hossain et al., ‘Prediction on domestic violence in bangladesh during the covid-19 outbreak using machine learning methods’, Applied System Innovation, vol. 4, no. 4, Dec. 2021, doi: 10.3390/asi4040077.

[15] M. Nayan et al., ‘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’, Asian Journal of Social Health and Behavior, vol. 5, no. 2, pp. 75–84, Apr. 2022, doi: 10.4103/shb.shb_38_22.

[16] R. Rois, M. Ray, A. Rahman, and S. K. Roy, ‘Prevalence and predicting factors of perceived stress among Bangladeshi university students using machine learning algorithms’, J Health Popul Nutr, vol. 40, no. 1, Dec. 2021, doi: 10.1186/s41043-021-00276-5.

[17] C. Ntakolia et al., ‘An Explainable Machine Learning Approach for COVID-19’s Impact on Mood States of Children and Adolescents during the First Lockdown in Greece’, Healthcare (Switzerland), vol. 10, no. 1, Jan. 2022, doi: 10.3390/healthcare10010149.

[18] A. Kumar, ‘Machine learning for psychological disorder prediction in Indians during COVID-19 nationwide lockdown’, Intelligent Decision Technologies, vol. 15, no. 1, pp. 161–172, 2021, doi: 10.3233/IDT-200061.

[19] A. Priya, S. Garg, and N. P. Tigga, ‘Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms’, in Procedia Computer Science, 2020, vol. 167, pp. 1258–1267. doi: 10.1016/j.procs.2020.03.442.

[20] A. Thiyagarajan, T. G. James, and R. R. Marzo, ‘Psychometric properties of the 21-item Depression, Anxiety, and Stress Scale (DASS-21) among Malaysians during COVID-19: a methodological study’, Humanit Soc Sci Commun, vol. 9, no. 1, Dec. 2022, doi: 10.1057/s41599-022-01229-x.

[21] Supervised and Unsupervised Machine Learning Algorithms-MachineLearningMastery.com’. https://machinelearningmastery.com/supervised-and-unsupervised-machine-learning-algorithms/ (accessed Nov. 22, 2022).

[22] F. Hutter, L. Kotthoff, and J. Vanschoren, ‘The Springer Series on Challenges in Machine Learning Automated Machine Learning Methods, Systems, Challenges’. [Online]. Available: http://www.springer.com/series/15602.

[23] D. Maclaurin, D. Duvenaud, and R. P. Adams, ‘Gradient-based Hyperparameter Optimization through Reversible Learning’.

[24] ‘The impact of COVID-19 on global health goals’. https://www.who.int/news-room/spotlight/the-impact-of-covid-19-on-global-health-goals (accessed Nov. 22, 2022).

[25] H. Onyeaka, C. K. Anumudu, Z. T. Al-Sharify, E. Egele-Godswill, and P. Mbaegbu, ‘COVID-19 pandemic: A review of the global lockdown and its far-reaching effects’, Sci Prog, vol. 104, no. 2, pp. 1–18, Jun. 2021, doi: 10.1177/00368504211019854/ASSET/IMAGES/LARGE/10.1177_00368504211019854-FIG3.JPEG.