

An Approach to Determine and Categorize Mental Health Condition using Machine Learning and Deep Learning Models

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ABSTRACT

The mental health of the human population, particularly in India during and after the COVID-19 pandemic is a major concern. All age groups have undergone mental stress during and after COVID-19, especially college students in urban areas and individuals belonging to the age group from 16 to 25. Early detection of mental stress among urban students will help in the resolution of major related issues that may hurt one's career. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have enabled the prediction of mental health status. Numerous studies have been conducted using various approaches, but there is still no agreement on how to predict mental symptoms across age groups. In the current study, proposed DL, Long Short-Term Memory (LSTM), and ML models, namely Support Vector Machine (SVM), ADA Boost, Random Forest (RF), K-Nearest Neighbor (K-NN), Logistic Regression (LR), and Multi-Layer Perceptron (MLP) are trained and tested on a real-world dataset. The DL LSTM model outperformed the conventional ML models with an accuracy of 100%.

Keywords-mental health; machine learning; health status detection; mental health data

I. INTRODUCTION

The COVID-19 pandemic had a negative impact on humanity in a variety of ways, including social, economic, physical, emotional, and psychological aspects. Specifically, elements related to changes in academic structures, tests, and a battle with limited resources can be directly associated with anxiety, tension, frustration, and depressive disorders during the COVID-19 lockdown period [1]. An ongoing influence on the mental health of students aged between 16 and 25 was observed. Students experienced significant psychological distress as a result of increased screen usage and frequent exposure to social media and COVID-19 news [2]. COVID-19 significantly influenced students' physical health, whereas the social distancing norms may have affected their psychological well-being [3]. Individuals, particularly students, express their thoughts and opinions on various social media platforms. The imposition of the lockdown to halt the pandemic's rapid spread caused psychological issues, such as despair and anxiety, in many students and also affected their life quality [4]. Younger people, particularly college students have considerably suffered in terms of their mental health as a consequence of numerous factors, involving their transitioning to new modes of instruction, loss of friend circles, cancellation of classes and

even entire semesters, financial hardships, shrinking job markets, failing relationships, etc. [5]. Many students experienced psychological issues as a result of the COVID-19 pandemic's spread, which impacted their academics as well as their overall personality [5]. Multiple factors, such as possible issues between students and teachers, lack of parental attention, bad eating habits, and lack of sleep can cause student stress, which is rather common among college students [6]. In July 2020, an online survey conducted by the Indian Psychiatry Society utilized the Depression Anxiety Stress Scale (DASS) 21 to gauge the mental health status of the Indian population amid the COVID-19 pandemic. The survey, distributed via WhatsApp through Survey Monkey, aimed to assess depression, anxiety, stress, and well-being among the public during the pandemic lockdown. Additionally, it included other psychological measures, namely the Patient Health Questionnaire-9, Generalized Anxiety Disorder-7, and Warwick-Edinburgh scale to comprehensively evaluate mental health [7, 8].

Authors in [9] investigated the effects of the COVID-19 pandemic and lockdown on the mental health of children and youth. The Short Self-Rating Questionnaire (SSRQ) was employed to evaluate the stress levels among individuals aged from 9 to 18 during this period. Utilizing an observational

approach with a descriptive cross-sectional design, the study conducted an online survey involving 369 schoolchildren. Stress levels were categorized as Low, Moderate, or Severe based on a scoring system and subsequent analysis. Authors in [10] compared the mental health symptoms and quality of life of frontline clinicians treating and not treating COVID-19 following the initial outbreak. They employed the Patient Health Questionnaire-9 (PHQ-9), Generalized Anxiety Disorder Scale-7 (GAD-7), Insomnia Severity Index (ISI), and World Health Organization Quality of Life Questionnaire-brief version (WHOQOL-BREF) to assess depression, anxiety, insomnia, and overall Quality of Life (QoL). Using a cross-sectional design with convenient sampling, the study was conducted between October 13 and 22, 2020, five months after China's first COVID-19 outbreak. Comparable groups were identified implementing Propensity Score Matching (PSM), whereas differences were analyzed deploying a Generalized Linear Model (GLM).

There is an upward trend in mental illness detection in the Natural Language Processing (NLP) research. Deep Learning (DL) methods receive more attention and outperform traditional Machine Learning (ML) methods [11]. Authors in [12] examined fear, depression, and anxiety symptoms among 324 college students in India during the COVID-19 pandemic. Utilizing a Google Forms questionnaire, the cross-sectional web-based survey included sociodemographic questions and psychometric scales. Results showed that 68.8% of students had a high fear of COVID-19, 28.7% experienced moderate to severe depression, and 51.5% had mild to severe anxiety. Additionally, the COVID-19 Fear Scale was moderately correlated with anxiety and depression scales. In [13], the COVID-19 impact on students, including changes in online learning, sleep patterns, and fitness routines, affecting weight, social life, and mental health, was highlighted. The findings emphasized the need for public officials to address COVID-19's adverse effects on learning experience.

Authors in [14] explored the psychosocial issues arising from academic stress in children and teenagers, and potential short and long-term psychological effects. A cross-sectional online survey of 4,342 Shanghai primary and secondary students from March 13 to 23, 2020, assessed psychological distress, life satisfaction, and the impact of home quarantine. Anxiety (24.9%), depression (19.7%), and stress (15.2%) were prevalent. Children experienced stress, missed growth opportunities, and lacked access to school meals [15]. A study in eastern India evaluated the impact of COVID-19 lockdowns on the mental well-being and behavior of children receiving psychiatric care. Conducted via telephone interviews from June 1 to July 8, 2020, the study involved 225 respondents using structured interviews based on established scales [16].

Authors in [17] examined the impact of stay-at-home orders on mental health, physical activity, screen time, and alcohol consumption among social work students. The results showed a significant increase in anxiety, depression, and screen time during the pandemic, highlighting the need for increased student support and implications for social work education [17]. In [18], the impact of the COVID-19 pandemic on university students in Malaysia was examined, focusing on

anxiety levels and influencing factors. A cross-sectional survey with 983 respondents employed Zung's self-rating anxiety questionnaire, revealing varying anxiety levels. Financial constraints, remote learning, and uncertainty about academics and careers were major stressors. In Northern New Jersey, a survey of 162 undergraduate students identified factors associated with mental health burdens during the pandemic using multivariable regression analysis [19]. Additionally, a study on 233 healthcare-related course students assessed lifestyle changes, mental health, and educational impacts [20].

Authors in [21] utilized EEG for dementia diagnosis and ML algorithms for predicting incidents in healthcare settings. An Artificial Neural Network model achieved 94.4% accuracy in classifying Lewy body dementia, while incident prediction models trained on 476 event reports exhibited a high accuracy of 93% on cross-validation [22]. Many researchers engaged ML and DL to accelerate COVID-19 detection, prevention, and treatment [23]. Authors in [24] aimed to detect dementia in MCI patients using EEG abnormalities. In [25], a DL model was employed to assess the mental state of social media users based on their posts. It accurately identified posts related to depression, anxiety, bipolar disorder, and BPD with high accuracy rates adopting Convolutional Neural Networks (CNNs). A system that detects depression through voice analysis using ensemble averaging of 50 1d-CNNs, fine-tuning model parameters through experimentation, and employing random sampling to enhance the training dataset was proposed in [26].

The main contributions of the current research article are:

- ML models were deployed to classify college students in the age group of 16 to 25 as stressed or not stressed.
- Accuracy and derived conclusions were compared across the ML models put into service.

Figure 1 displays the followed methodology.

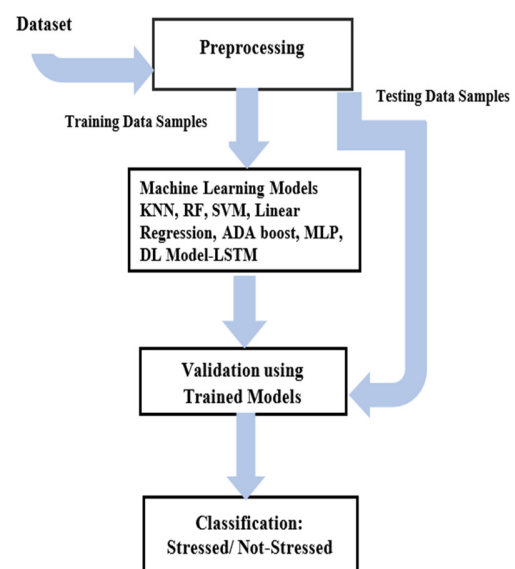


Fig. 1. The methodology used.

II. DATASET CREATION

We utilized our own real-world dataset, generated from answered questionnaires from student participants. The dataset consists of behavioral data with 10 attributes. The dataset was composed of the following fields:

- A1: Do you immediately respond when someone is calling your name?
- A2: Do you have difficulty in maintaining eye contact?
- A3: Do you respond positively when something is required from you?
- A4: Do you have common interests with parents/staff?
- A5: Have you pretended to study, work, or read from the laptop or mobile phone?
- A6: Do you show any interest in your peers company?
- A7: Do you comfort your peers when in difficulty?
- A8: Do you recall initial and earlier sessions?
- A9: Do you use simple gestures?
- A10: Do you stare blankly at nothing?

The total number of answered questionnaires was 1054, out of which 326 were considered as stressed and 728 as not stressed, based on their answers.

III. THE CONSIDERED MODELS

This article proposes models for predicting and detecting the mental health state using ML and DL models, as well as solutions to challenges encountered in previous attempts. Six different ML models and a DL model were considered and compared. Conclusions were drawn based on the prediction outcomes. Support Vector Machine (SVM), Random Forest (RF), AdaBoost, Logistic Regression (LR), k-Nearest Neighbor (KNN) algorithm, and Multi-Layer Perceptron (MLP) are the ML models used whereas LSTM is the DL model employed. The proposed ML and DL models, which aim to classify whether a student is stressed or not are described below.

A. Machine Learning Models

1) Support Vector Machine

SVM is an example of a supervised ML technology that can be used to solve problems of classification and regression. It is typically employed in classification projects.

2) Random Forest Algorithm

A group learning algorithm, RF utilizes a random sampling technique. RF can be deployed for classification, regression, and other purposes.

3) AdaBoost Algorithm

Adaptive Boosting (AdaBoost) is an approach to ensemble modeling that utilizes many relatively weak classifiers to create a single, robust one. A model is built using weak series models. AdaBoost was the first algorithm created to improve binary classification accuracy.

4) k-Nearest Neighbor Classifier

The KNN technique is a straightforward method for storing all known instances and categorizing new cases in accordance with a similarity metric (e.g. distance functions). Since the early 1970s, KNN's non-parametric technique has been implemented for statistical estimation and pattern recognition. KNN is a simple ML technique that may be used for both classification and regression.

5) Logistic Regression

LR, commonly known as the logit model or logit regression, is a statistical model employed to make educated guesses about the likelihood of an event occurring in the presence of known background information. LR relies on binary data, which can either be "true" (1) or "false" (0).

6) Multi-Layer Perceptron

An MLP is a feed-forward ANN that generates a set of outputs from a set of inputs. An MLP is characterized by several layers of input nodes connected as a directed graph between the input and the output layers.

B. The Long Shot Term Memory Deep Learning Model

The purpose of LSTM is to model and forecast data sequences. It is appropriate for tasks where the sequence of the data is important since it can capture temporal dependencies in the input data. Long-term information retention is possible in the memory cells found in LSTM networks. These memory cells consist of many gates that control the information flow in addition to a cell's state. LSTM is characterized by input, output, and forget gates. The forget gate establishes which data from the preceding time step ought to be ignored or forgotten. It creates a forget vector by multiplying the current input by the prior concealed state element by element. Which new data from the current time step should be added to the cell state is decided by the input gate. It creates an input vector by using the current input and the prior concealed state as inputs. The output gate is responsible for selecting which data from the cell state should be sent to the following concealed state. It creates an output vector, or the LSTM cell's output, by using the current input and the prior hidden state as inputs. The following equations fulfil the specific function assigned to each gate [27].

$$F_i = \sigma(W_f \cdot h_{i-1} + W_f \cdot x_t + b_f) \quad (1)$$

$$I_i = \sigma(W_i \cdot h_{t-1} + W_i \cdot x_t + b_i) \quad (2)$$

$$O_i = \tanh(W_o \cdot h_{i-1} + W_o \cdot x_t + b_o) \quad (3)$$

$$C_i = f_i * c_{t-1} + I_i \cdot \tanh(W_c \cdot [h_{i-1}, x_i] + b_c) \quad (4)$$

$$H_t = O_i * \tanh(c_t) \quad (5)$$

where F_i is the forget gate at timestep i , I_i is the input gate at timestep i , O_i is the output gate at timestep i , c_{t-1} is the state of the previous cell, h_{t-1} is the state of the previous hidden cell, C_i is the state of the current cell, H_t is the state of the current hidden cell, σ is the sigmoid function, \tanh is the hyperbolic tangent function, b_f, b_i, b_o are the biases at the forget, input, and output gates, and W_f, W_i, W_o the respective weights. The hidden layers of the proposed model had 100, 50, and 30 nodes.

C. Design of the Proposed Models

In the above-proposed model, the dataset has been pre-processed to remove redundant data and was split into training and testing sets with split ratios of 80:20 and 70:30. The training dataset has been fed into the ML models (KNN, RF, SVM, LR, AdaBoost, and MLP) and into the DL LSTM model followed by the testing that has been carried out using trained models with testing samples. The confusion matrices for the ML classifiers for the 70:30 split ratio are depicted in Figures 2-7.

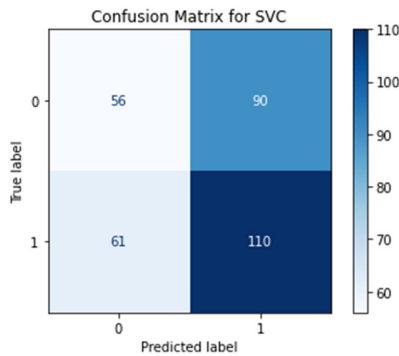


Fig. 2. Confusion matrix of the SVC model.

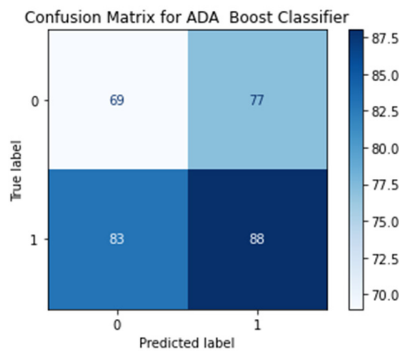


Fig. 3. Confusion matrix of the AdaBoost model.

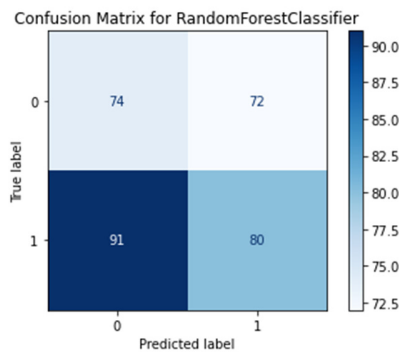


Fig. 4. Confusion matrix of the RF model.

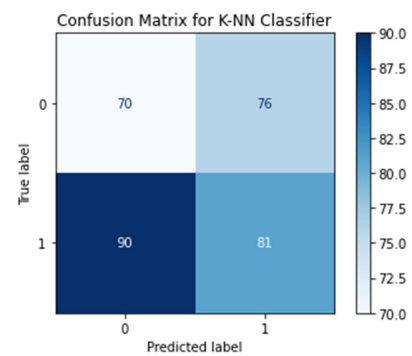


Fig. 5. Confusion matrix of the KNN model.



Fig. 6. Confusion matrix of the LR model.

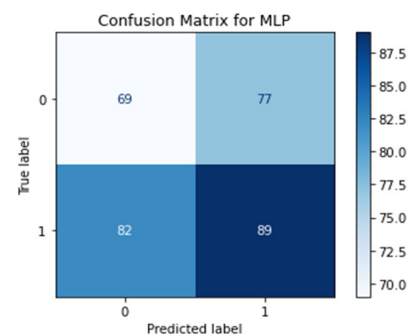


Fig. 7. Confusion matrix of the MLP model.

The training data set was used to train the seven models. The LSTM model had 100, 50, and 30 nodes in each hidden layer. The trained models were tested on the testing dataset. The pre-trained ML and DL model outputs are portrayed in Tables I and II. If the testing accuracy score is lower than the training accuracy score, the following calculations are performed:

$$Combined_Result = \sum (testing_accuracy_score_i \times prediction_of_algo_i) \quad (6)$$

It is observed in Tables I and II that the best accuracy (100%) was obtained for LSTM. The DL LSTM model (with 500 epochs) outperformed the ML models in both considered split ratios. The ROC curves for the proposed models are in Figures 8-14. The accuracy of the proposed models is compared in Figure 15.

TABLE I. PERFORMANCE COMPARISON OF THE CONSIDERED MODELS WITH 80% TRAINING-20% TESTING DATASET SPLIT RATIO

Model Name	Precision	Recall	F1-score	Training accuracy	Testing accuracy
SVM/SVC	0.55	0.57	0.56	0.54	0.48
ADA Boost	0.42	0.48	0.45	0.69	0.49
RF	0.54	0.43	0.48	0.52	0.46
KNN	0.55	0.47	0.50	0.70	0.47
LR	0.55	0.57	0.56	0.55	0.49
MLP	0.58	0.52	0.55	0.93	0.52
DL model-LSTM	1.0	1.0	1.0	1.0	1.0

TABLE II. PERFORMANCE COMPARISON OF THE CONSIDERED MODELS WITH 70% TRAINING-30% TESTING DATASET SPLIT RATIO

Model Name	Precision	Recall	F1-score	Training accuracy	Testing accuracy
SVM/SVC	0.55	0.64	0.59	0.53	0.52
ADA Boost	0.45	0.47	0.46	0.71	0.50
RF	0.52	0.46	0.49	0.90	0.48
KNN	0.51	0.47	0.49	0.72	0.48
LR	0.55	0.67	0.61	0.54	0.43
MLP	0.56	0.55	0.56	0.98	0.52
DL model-LSTM	1.0	1.0	1.0	1.0	1.0

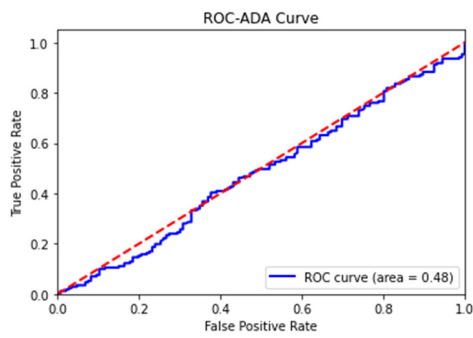


Fig. 8. ROC curve of the AdaBoost classifier.

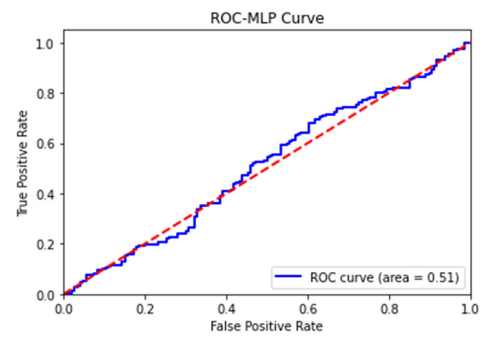


Fig. 11. ROC curve of the MLP.

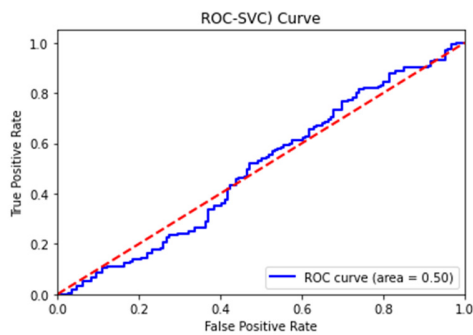


Fig. 9. ROC curve of the SCV classifier.

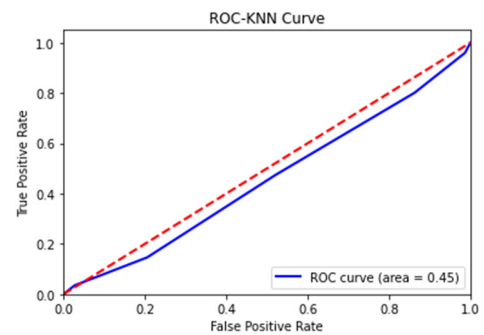


Fig. 12. ROC curve of the KNN classifier.

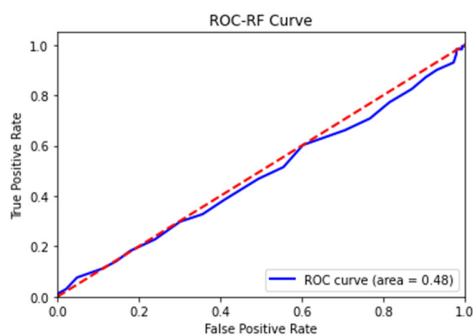


Fig. 10. ROC curve of the RF.

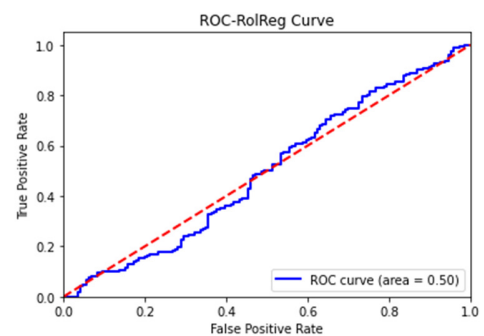


Fig. 13. ROC curve of the LR.

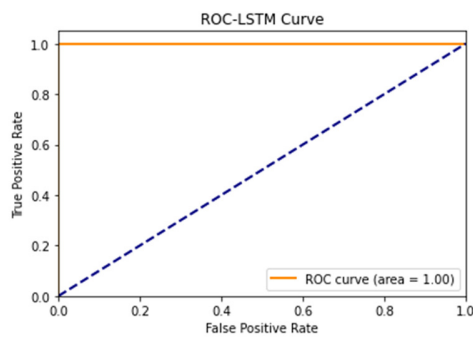


Fig. 14. ROC curve of the LSTM model.

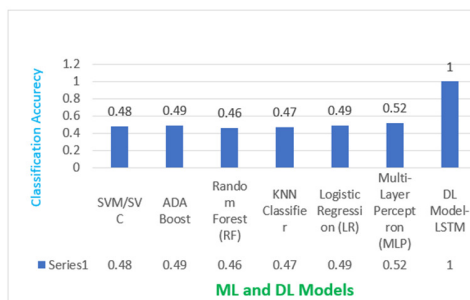


Fig. 15. Accuracy comparison.

IV. CONCLUSION

Considering the COVID-19 pandemic, this study suggests applying realistic Deep Learning (DL) and Machine Learning (ML) models with the purpose of identifying mental stress in students. Not only do these models aim to identify indicators of mental stress, but also to avert negative consequences. The specific models have the potential to save lives by greatly influencing the efficacy of therapies and treatments and quickly identifying severe cases of mental stress. The main goal was to create an efficient DL Long Short-Term Memory (LSTM) model. To accomplish this, a sophisticated architecture with hidden layers made up of 100, 50, and 30 nodes was used. This model was proven to perform better than other established ML models, such as Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN), Logistic Regression (LR), AdaBoost, and Multi-Layer Perceptron (MLP), through extensive testing and evaluation. The study indicates that these models have a lot of potential in helping young people who are experiencing mental stress. It is anticipated that the results of the current study and the debate that follows will make a substantial contribution to the field and offer insightful information for further research. With the suggested hidden layer architecture, the deep learning LSTM model notably achieves a remarkable accuracy rate of 100%, demonstrating its potential to completely transform mental health interventions and diagnostics.

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