Student Stress Prediction Using Machine LearningAlgorithms And Comprehensive Analysis

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Abstract:
Student performance is most often hampered by mental health difficulties. Students' motivation, attention, and social ties can all be impacted by mental illness, all of which arekey factors in their academic achievement. Due to the novel coronavirus pandemic, many institutions and colleges throughout the world have resorted to online learning. Despite widespread use of emergency remote learning (ERL) in higher education during the COVID-19 pandemic, little is known about the elements that influence student satisfaction and stress levels in this innovative learning environment in a crisis. Our research intends to provide a timely assessment of the COVID-19 pandemic's impact on college students' mental stress level employing machine learning algorithms to predict the stress faced by students based on their academic routines. Data collected through student surveys relating to a lot of factors such as time spent on studying, social media, health andfitness etc. provide a strong basis to determine students stress levels and via supervised machine learning algorithms predictions are done on the academic stress by analyzing the prime factors affecting the issue at hand. Various ML models such as Naive Bayes, Random Forest, Artificial Neural Networks (ANN) etc. have been employed and a comprehensivecomparison is performed with the proposal of the most optimum algorithm for the prediction of stress level.

Keywords: Emergency Remote Learning, COVID-19, Machine Learning, Stress Level, Naïve Bayes, Artificial Neural Networks.

DOI Number: 10.4704/nq.2022.20.14. NQ880126 **NeuroQuantology 2022; 20(14):895-906**

I.INTRODUCTION

In December 2019, the Coronavirus Disease 2019 (COVID- 19) was originally recognised as pneumonia of unknown origin in Wuhan, Hubei Province, China. The causative agent of COVID-19 is later identified as a new coronavirus, severe acute respiratory syndrome coronavirus (SARS– CoV2), by the International Committee on Virus Taxonomy (ICTV) [1]. Because the COVID-19 outbreak spread not justin China but also around the world, the World Health Organisation (WHO) declared it a pandemic on March 12, 2020. As of August 25, 2020, the total number of confirmed cases and fatalities in 216 nations was 23,491,520 and 809,970, respectively [2]. To combat the possibility of disease spreading, the government has taken a number of steps. Travel restrictions, forced travel quarantines, social distance, bans on public gatherings, school and university closures, company closures, self-isolation, requiring people to work from home, curfews, and lockdown are examples of these methods. Authorities in a number of nations aroundthe world have imposed a lockdown or curfew to halt the spread of the virus [3]. These policies have a negative impact on business, education, health, and tourism around the world [3]. The COVID-19 pandemic has impacted students at all levels of school. Around the world (in 192 countries), educational institutions have either temporarily shuttered or imposed localised closures, affecting around 1.7billion students. Many institutions throughout the world have postponed or canceled all campus activities in order to reduce the

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Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

number of people who are exposed to the virus. These policies, on the other hand, have greater economic, medical, and social consequences for both undergraduate and postgraduate populations. This kind of instruction offers an option to minimise either student-to-student contact or student-to-lecturer contact. However, due to the economic and digital divide, many students do not have access to online education due to a lack of either the means or the equipment. Due to the suspension of classroom instructionin many colleges and institutions, undergraduate and graduate students can now benefit from online instruction.
The COVID-19 pandemic has raised attention to the mental health of those who have been impacted. Anxiety and fear for oneself or loved ones, limits on physical movement and social activities due to quarantine, and abrupt and dramatic lifestyle changes are all known to intensify or create new stresses during epidemics [4]. Infection worries, frustration, boredom, insufficient resources, insufficient information, financial loss, and stigma were all recognised stresses in a recent assessment of virus outbreaks and pandemics [5].
Academic achievement is most often hampered by mental health difficulties. Mental illness can have an impact onstudents' motivation, attentiveness, and social connections, all of which are important variables in their academic success [6].

In a wide range of industries, machine learning (ML) techniques are frequently used to propose reliable solutions. Machine learning is a technique where the system continuously develops based on data that has already been processed. With the help of these algorithms, the collected data can be learned effectively both supervised and unsupervised [7]. Artificial intelligence (AI) is being usedby mental health practitioners to increase the precision of diagnoses and treatments. To help with their overburdened workloads, therapists are turning to AI. The need for anxiety therapies has increased, according to 84 percent of psychologists [8]. Machine learning models that are developed using physiological reactions to stress andemotional stimuli have been used in recent years to automate the prediction and detection of stress [9]. Various different ML models such as Naive Bayes, Random Forest, Artificial Neural Networks (ANN) etc have been employed and a comprehensive comparison is performed with the proposal of the most optimum algorithm for the predictionof stress level [10]. Our research intends to provide a timely assessment of the COVID-19 pandemic's impact on college students' mental stress level employing machine learning algorithms to predict the stress faced by students based on their academic routines. Data collected through student

II. LITERATURE SURVEY

There have been numerous studies done on the use of machine learning algorithms to predict mental health illness which have had recent success.

This narrative review [11] examines the most recent studies on the effects of academic-related stress on students' learning capacity and academic performance, as well as mental health issues such as melancholy and anxiety, sleep disorders, and drug abuse. Students' learning capacity, academic performance, education and employment attainment, sleep quality and quantity, physical health, mental health, and drug use outcomes have all been shownto be negatively impacted by persistent educational stress. Akey goal for change is to improve students' stress- management skills and talents.

At-home distractions (including disruptions from other family members and additional chores) are a substantial difficulty for college students learning from home during COVID-19, according to preliminary research [12]. These issues, when considered collectively, are likely to cause severe academic stress and uncertainty. COVID-19 and its accompanying disturbances have been linked to large increases in stress, anxiety, sadness, and suicidality in college students, according to one study. These findings imply that some students may be particularly vulnerable to academic stress and emotional distress as a result of the epidemic, emphasizing the urgent need for intervention and preventative initiatives.

In the context of the COVID19 epidemic, this study looked at the links between three essential stressors and two categories of health in Chinese college students. Academic workload, remoteness from school, and fears of contagion all had negative consequences on college students' healthvia perceived stress, according to the findings of this study. Multiple prevention and control methods aimed at college students during the COVID-19 issue may result in varying degrees of stress and health problems. The current study sought to fill that gap by focusing on college students and investigating the impact of many major stressors on their health during the COVID-19 outbreak [13]. Specifically, we identified three important stressors among college students academic workload, separation from school, and fear of surveys relating to a lot of factors such as time spent on studying, social media, health and fitness etc. provide a strong basis to determine students stress levels and via supervised machine learning algorithms predictions are doneon the academic stress by analysing the prime factors affecting the issue at hand. pandemic's impact on college students' mental stress level employing machine learning algorithms to predict the stress faced by students based on their academic routines. Data collected through student surveys relating to a lot of factors such as time spent on studying, social media, health and fitness etc. provide a strong basis to determine students stress levels and via supervised machine learning algorithms predictions are doneon the academic stress by analyzing the prime factors affecting the issue at hand. Contagion and further explored the mechanism behind the relationships between three stressors and mental and physical health.

The purpose of this research [14] is to investigate the impactof stress on the academic performance of University of CapeCoast School of Business students, as well as the risks that come with it when stress is not properly managed. Three (3) research questions were examined to reach this goal, and theliterature analysis was mostly focused on the causes, effects, and approaches to manage academic stress. According to the findings of the study, students at the University of Cape Coast School of Business encounter varying degrees of academic stress, which has an impact on their academic performance. The study identified symptoms and signals that can be used to identify kids who are experiencing academic stress. These included not getting enough sleep, feeling fatigued during the day, and feeling ill on occasion. Students feel academic stress has a significant impact on their performance, according to the study's findings. Stress causes students to miss class, lowers their academic morale, and causes them to fail to complete tasks on time. As a result, academic stress has a negative correlation with student performance. The more stressed a youngster is, the worse he or she will do at school.

The prevalence of stress, anxiety, and depression amongundergraduate students at a public research university during the six weeks following the COVID-19 epidemic, as well as their use of mental health services, are described in this study [15]. We examined stress, anxiety, and depressionlevels with well-established clinical measures and inquired how many college students accessed on-campus and off- campus mental health services during the academic yearusing a self-administered online survey. Our findings found that more than eight out of ten students polled were stressed in some way, and 36–44 percent of those surveyed had moderate or severe anxiety or depression. More over 60% ofstudents with moderate or severe stress, anxiety, or depression, on the other hand, had never sought out mental health treatments on or off campus.

The current study was a descriptive study that used a survey method to collect quantitative data [16]. The goal of this study was to look at the levels of academic, social, psychological, physiological, and environmental stress among college students. In addition, the study investigated the relationship between a student's total stress level and their gender and cumulative GPA. The majority of students had moderate to high levels of academic and environmental stress, but low levels of psychological, social, and physiological stress, according to the findings. The current study also revealed that the gender and cumulative GPA of students had no statistically significant relationship with their overall stress scores. According to this study, the majority of College of Education students are under moderate stress. It also revealed that environmental and academic stressors were found to be more prevalent among pupils. Academic stressors that inflict severe academic stress include a lack of fair grading, academic overload, trouble dealing with one's academic challenges, and poor subject matter and pedagogical competency of teachers. [7]

In response to the pandemic's disruptions, higher education institutions all across the world switched to e-learning. While e-learning offers the advantage of allowing students to attend classes from anywhere at their leisure, the unexpected disruptive change to e-learning during the pandemic presented students with numerous obstacles, many of which had the potential to cause mental healthissues among the students. The goal of this study was to see how COVID-19-induced e-learning affected university students' stress perceptions in Oman [17]. Students havebeen absent from physical campuses for almost a year, yet they are still completing their courses and programs online. The multiple obstacles they face as a result of e-learning, along with the surrounding uncertainty, has increased their stress levels. Continued stress will have an impact not just on their academic performance, but also on their mental and physical health, as stress has been identified as one of the leading causes of a variety of physical and mental problems.While e-learning appears to be becoming the new normal, students deserve adequate attention, assistance, and support from their families and institutions. To avoid overstressing students, schools should review their online course and programmed delivery systems, techniques, and practices.
It has also been blamed on a lack of parental attention for the attacks on all students. Children often do not pay attention to their eating habits, and as a result, they are more prone to stress. In addition, poor sleep is another prevalent cause of stress, and students all over the world are affected by it.

This research tries to understand the effects of stress on students and the importance of managing it in order to improve learning outcomes [18]. The study's conclusion is that students' stress levels are quite high, and that their stresslevels are rising as the days pass. Students also use coping tactics such as yoga, exercise, and diversion therapy, which includes spending time with family and watching television.Academic, environmental, social, and health issues all contribute to the emergence of stress. Academic variables are the most significant stressors, necessitating the implementation of particular and focused interventions to significantly reduce the load of stress on students. Teaching methods and college environments should be tailored to the students' needs. The productive utilization of existing student welfare systems, development of more 'student- friendly' environments and regular periodic extracurricular activities with universal participation can prove to be useful stress-busters.

The COVID-19 epidemic has had multiple effects on students: dangers to their own and their families' health,school closures, and the shift to online learning in March 2020, a lengthy summer of physical separation, and then the struggle of returning to school in fall 2020. During the first several weeks of school in fall 2020, around 2,000 12- to 18-year-old Alberta students participated in the current study [19]. In the first few weeks of September, students took an online survey regarding their perceptions of COVID-19, their fall return-to-school experiences (84.9 percent returned in person), their self-reported pandemic- related stress, and their behavior, affect, and cognitive performance. Students expressed anxiety about their health, family confinement, and keeping social interaction in moderate to equal amounts. Student stress levels were likewise over critical thresholds in 25% of the sample, with females and older adolescents (ages 15–18 years) reporting higher stress indicators than men and younger adolescents (ages 12–14 years). Stress indicators were positively and significantly correlated with self-reported behavioral concerns (i.e., conduct problems, negative affect, and cognitive/inattention), and stress arousal (e.g., sleep problems, hypervigilance) explained significant variance in behavioral concerns, according to multivariate analysis.

Simulations evaluating the probable impact of COVID-19- related school closures on education and learning outcomes have been made, according to the aforesaid research study [19]. It explores four scenarios, each with a different period of school closures and the effectiveness of any mitigating actions implemented by governments. School closuresmight result in a loss of 0.3 to 1.1 years of schooling adjusted for quality, lowering the effective years of basic schooling that kids acquire during their lives from 7.8 to 6.7 to 7.5 years. The models mentioned in the study imply that the world is on track to experience a significant setback in its objective of decreasing the number of learning poor by 2030 unless dramatic corrective action is implemented. If adequate policy measures are not developed, a persistent learning crisis may be aggravated. Hence concluding that appropriate steps must be taken to accelerate learning by constructing more equitable and resilient post-COVID education systems that allow children to study constantly both in school and at home.

The impact of school closures on primary school performance is examined in this research. Students' progress in national examinations taken before and after the lockdown was compared to the same time in the preceding three years. This study examined particularly detailed data on primary school students in the Netherlands, and there is convincing evidence that students learn less under lockdownthan during a standard school year [20]. These reductions may be seen over the whole age range investigated in all three subject areas: mathematics, spelling, and reading. The findings suggest that learning loss was most evident forstudents from low-income families, confirming many people's predictions that school closures would increase socioeconomic divides. The findings show that kids made little or no progress while learning at home, and they suggest that losses may be substantially worse in nations with poor infrastructure or extended school closures.

The purpose of this research was to do a meta-analysis of peer-reviewed published papers on the burden of psychological indicators among college students in the aftermath of the COVID-19 epidemic [21]. The main worries among a subset of college students were found to be pressure to achieve, educational performance, and post- college graduation plans. These difficulties expose these kids to discomfort and its harmful consequences, such as depression, anxiety, insomnia, suicidal thoughts, and the adoption of maladaptive behaviors. College students' mental health difficulties are frighteningly high, particularly in the United States, with eight out of ten students having regular stress episodes in 2019. Furthermore, young people likesocializing and engaging in parties and festivities, which have been curtailed during epidemic times, increasing to their dissatisfaction. Some adolescents who get counselling services have not received such assistance. Students with part-time jobs have lost their jobs during COVID-19, incurring financial hardship. The outcomes of this study highlight the need of developing suitable public health treatments to meet adolescents' emotional, psychological,and social needs.

The article focuses on the effects of lockdown on individuals, particularly students. Traumatic occurrences, such as the COVID-19 epidemic, are said to have generated psychological distress and anxiety symptoms, which have a poor influence on sleep quality [22]. As a result, the authors of this report centered on physical and mental health, as wellas sleep, during the COVID-19 disaster. Employees had a prevalence of maintenance insomnia of 24 percent prior to COVID-19, which increased dramatically during COVID-19to 40 percent, whereas workers with difficulty initiating sleep were only 15 percent, which climbed to 42 percent. The purpose of this study was to examine the psychological impact of the COVID-19 emergency period on a sample of administrative personnel and students. The authors concentrated on subjective sleep quality and psycho- emotional well-being in particular. The impact of social isolation on emotions of loneliness, vulnerability, and emergency fear may have made young people feel less effective in overcoming the situation, resulting in a rise in anxious and depressed symptoms.

The authors record disturbances in physical activity, sleep, and time utilization among young adults during the outset ofthe pandemic and investigate the association between these disruptions and mental health in this research [23]. Theyfirst undertake a longitudinal study to see how physical activity and mental health have changed throughout the pandemic in comparison to both pre-pandemic levels and prior cohorts. Second, survey measures of mental well-being and social distancing have been connected to biometric measurements of physical activity and sleep. This method enables the researchers to explore depression risk variables during COVID-19 and compare them to depression predictors earlier to the pandemic. According to the findings of this article, interruption to physical activity is a major risk factor for depression during the pandemic.

In this article, the mental stress of students is calculated one week before the exam and while using the internet. The goal was to examine stress in college students at various periods in their lives [24]. According to the authors, the influence that test pressure or recruitment stress has on the student is immense, hence they conduct a study on how these elements affect the mind of a student while associating this stress withthe time spent on the internet. This study looks at how these things affect these people's psyches by using their mindwave flag from the PSS dataset. The researchers' primary focus was on the PSS (Perceived Stress Scale) test and the effects it had on the individual. They worked with PSS to some level in order to examine an individual's psychologicalcondition. Four machine learning methods (Random Forest, Nave Bayes, Support Vector Machine, and K-Nearest Neighbor) were used in this work, and their specificity, sensitivity, and accuracy were determined. With this, if a person is under severe mental stress, an initial analysis can be performed to assist him or her in the early phases of stress.

This study discusses the mental health issues that students in higher education face [25]. Different research publications were evaluated to identify research gaps. A review of mental health problems among higher education students and the related variables illustrates what happens to students who have mental health difficulties. Furthermore, it provides more information on the elements that contribute to mental health concerns among students. Supervised learning is one of the most often used data mining approaches for resolving difficulties with the categorization of mental health concerns. The most well-known method is the support vector machine (SVM), which is followed by the decision tree and neural network. SVM demonstrated remarkable accuracy ranging from 70% to 96%. According to the authors, the most typical variables are a lack of social support, a financial hardship, and a learning environment.

The key objective of this report was to analyze the effects of a complete shutdown during COVID-19 on learners' education and overall stress, as well as to achieve a high level of education and student accomplishment. A machine learning approach was utilized to evaluate the number of online courses taken that focus on contextual information [26]. A survey was carried out using a series of questions ona form based on their personal experiences. There was atotal of 45 questions posed, with responses from participantsdivided into two categories: those gathered before to online courses and those collected during online courses. The authors mention that the learners' stress can be induced by technological communication, interpersonal relationships, perspectives, instructional techniques and overall stability. [18]

According to the study, to collect the dataset needed for this research, an online survey was undertaken [27]. The survey questionnaire included 38 questions categorized into 5 major categories: basic information about the responding students, information about their digital connectivity, social lives, online learning experiences, engagements, overall mood, and thoughts during the period of national lockdown due to COVID-19. Using R and Python scripts, the survey responses were analyzed and shown. MS-Excel was used for certain visuals as well. According to the reports, 69.8 percent of students miss seeing their friends in person, indicating that the lockdown has had a significant impact on their social life. The results also reveal that students believe that while online education may augment classroom instruction, it cannot replace the experience, learning and face-to-face interactions that occur in the classroom environment.

The authors of this article provide the findings of an online- based questionnaire study that examined the influence of the COVID-19 pandemic's lockdown, house confinement, and social isolation on people's well-being and lifestyle patterns [29]. The length and quality of sleep were studied and shown. Excessive screen time appears to have had a negative impact on health by disrupting sleep patterns and duration. This is due to the blue light generated by their gadgets' screens when used at night suppressing melatonin synthesis. Blue light exposure before night has been linked to sleep inefficiency and shortened sleep duration in both adults and children. The study also found that a substantial number of people reported feeling tired at an odd time of day, and that their sleep was likely influenced by mental stress, worry, and screen use before bedtime. The researchers concluded that sleep is essential for physicalhealth and the proper functioning of the immune system. It is also an important promoter of emotional wellbeing and mental health, and it aids in the reduction of stress, depression, and anxiety.

III.DATASET USED

An online poll with students as the intended population was used to acquire the dataset. The purpose of this survey was to gather information about how COVID 19 influenced everyone's life over the course of two years and how it continues to affect them [30]. The dataset is based on a survey of 1195 students and is classified based on characteristics such as area of residence, age, amount oftime spent on online class, time spent on self-study, andtime spent on social media, weight change before and after COVID, and health conditions. Some of the features utilizedto predict using the model are as follows: 'Age of Subject', 'Time spent on Online Class', 'Time spent on self-study', 'Time spent on fitness', 'Time spent on social media', 'Time spent on TV', 'Number of meals per day', 'Region of residence Outside Delhi-NCR', 'Rating of Online Class experience Excellent', etc.

Sr. No	Attribute Name	Data Type
1	Region Of Residence	Object
2	Age Of Subject	Int64
3	Time Spent on Online Class	Object
4	Medium Of Online Classes	Object
5	Rating Of Online Classes	Object
6	Time On Self -Study	Float64
7	Time On Fitness	Float64
8	Time On Sleep	Float64
9	Time On Social Media	Float64
10	Time Spent On TV	Float64
11	Change In Weight	Float64
12	Mental Health Issue	Object
13	Connection With Family	Object
14	No. Of Meals Per Day	Object
15	Stress Busters	Object

Table. 1: Dataset Attributes

IV. DATASET PREPROCESSING

The data is first preprocessed before performing the predictive analysis using ML algorithms. Initially the null values in the data set are identified and removed appropriately and the outliers are eradicated to ensure data conformity. Most of the data collected through the survey was categorical data which had to be encoded for the ML algorithms to work with. The categorical attributes are first identified and are encoded accordingly. This allows the ML algorithms to work with numbers rather than texts which make the classification mechanism more streamlined and efficient. Once the data is cleaned and encoded appropriately, feature selection is then performed in which obsolete attributes to the problem statement such as, "what do you miss the most", "ID" etc. and the data is split into independent and dependent variables. Standard scalar is applied to the independent variables. Many machine learning estimators require attribute standardization becausethey may perform poorly if the individual features do not more or less resemble standard normally distributed data.

Finally, the data is split into training and testing data with about 30% of the data being the testing dataset and remaining 70% being used as the training data for the most accurate results.

V. PROPOSED ARCHITECTURE MODEL

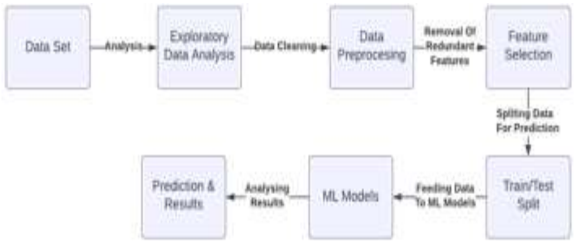

Fig.1: Architecture Model

The above diagram represents the overall architecture diagram of the proposed work. The data extracted from the survey is first normalized and a comprehensive exploratory data analysis through different data visualization techniques is performed to understand the trends and gain valuable insights required to perform feature selection. Data preprocessing follows next with the removal of null data, encoding and identification of categorical data and data sampling. The redundant features are then removed during the feature selection process as well as the dependent and independent variables are identified to create the datasets tobe fed to the ML model. The data is then split into training and testing data for the prediction processes. Different ML models are employed with different prediction methodologies and finally the results are analyzed, and the most optimum ML algorithm is suggested.

VI. METHODOLOGY

A. Random Forest

A supervised learning algorithm is random forest. It comes in two different forms; one is used to solve classification problems, the other to solve regression issues. One of the most adaptable and user-friendly algorithms is this one. On the basis of the provided data samples, it constructs decision trees, obtains predictions from each tree, and votes for the top solution. It also serves as a fairly accurate measure of feature importance. The Random Forest algorithm creates a forest of trees by combining various decision-trees, hence the name. The accuracy of the random forest classifier increases with the number of trees in the forest. In the model used with this data, the accuracy level achieved is 84 percent. Here the trees we are building before taking an average estimation are around hundred. We take different features in the dataset which includes age of subject, time spent on online class etc. to decide if the particular subject has a mental health issue.

B. Artificial Nerual Network Model With Desnse Net

Artificial neural networks (ANNs) employ learning algorithms that enable them to autonomously adjust—or,in a sense, learn—as they are presented with fresh data. As a result, they are an excellent tool for modelling non-linear statistical data. The model has 100 epochs, and theaccuracy obtained with those is 96%. The accuracy of this model is 81 percent. 32 has been chosen as the batch size for this model. After conducting a search using the grid approach, the ultimate accuracy is 80%.

C. Naïve Bayes Algorithm

Naive Bayes techniques are a type of supervised learningalgorithms that employ Bayes' theorem with the naive assumption of conditional independence between every pair of features given the class variable value. It is termed Naive because it believes that the presence of one trait is unrelated to the occurrence of others. For example, if a fruit is classified based on color, shape, and flavor then a red, spherical, and delicious fruit is identified as an apple. As a result, each characteristic helps to identifying it as an apple independently of the others. It is termed Bayes because it is based on the Bayes' Theorem. Bayes' theorem, often known as Bayes' rule or Bayes' law, is a mathematical formula used to calculate the probability of a hypothesis given past knowledge. It is determined by the conditional probability. It entails the following steps: 1) Pre- processing of data. 2) Fitting Naive Bayes to the Training data set. 3) Predicting the test result. 4) Determine the result's accuracy (Creation of Confusion matrix). 5) Displaying the results of the test set.

D. Logistic Regression Model

Based on a given dataset of independent variables, logistic regression calculates the likelihood that an event will occur, such as voting or not voting. Given that the result is a probability, the dependent variable's range is 0 to 1. In logistic regression, the odds—that is, the probability of success divided by the probability of failure—are transformed using the logit formula. The natural logarithm of odds or the log odds are other names for this. Logistic function is represented by the following formulas:

Logit pi) = 1/ (1+ exp (-pi)) ln (pi/ (1-pi)) = Beta_0 +Beta_1*X_1 + … + B_k*K_k

E. Support Vector Machine

Lastly, SMV was used since it performs best for classification when there is a discernible margin of dissociation between classes. Even when the data are nototherwise linearly separable, the approach maps the datato a high-dimensional feature space so that data points can be categorized. It operates by identifying the ideal hyperplane that divides each data point into its respective classes. The categorization of stress-related symptoms in the suggested work may be done with high accuracy due to the differences existing among the data attributes and minor correlations, as evidenced by the F1-score achieved by the SVM algorithm of roughly0.90.

VII. RESULTS AND ANALYSIS

Analysis of all ML models' performance reveals that majority of them had high accuracy scores, according to the findings. Based on the characteristics used, the ML models were successful in classifying the students' levels of stress. As the ML model with the greatest accuracy score 90% for the classification, Support Vector Machine was adopted. It was able to outperform the other ML models because of its classification concept, which is based on identifying theideal hyperplane that divides each data point into its respective classes. Both the Random Forest algorithm and ANN, with accuracy scores of around 83 and 86 percent, performed well. The Naive Bayes algorithm has the lowest accuracy score, with just 20%. The Naive Bayes classifier performs poorly if the training data and test set have distinct frequency distributions. Values that are underrepresented in the training set have a particularly negative impact on the classifier. As a result, it can be said that the Logistic Regression model is the best ML method for the given issue statement. The correctness of the suggested study is more trustworthy and accurate when compared to related workthat has been addressed.

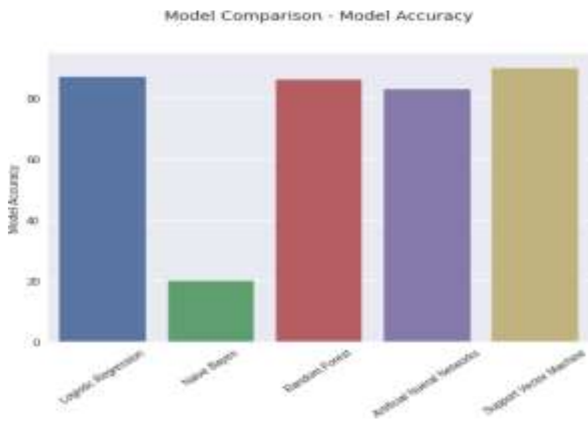

Fig. 2: Model Performance Comparison

As seen in Fig.2 SVM algorithm works the best while both Logistic Regression and Random Forest models performed equally well. Naïve Bayes algorithm underperformed. This is primarily because of the Naive Bayes conditional independence assumption, which states that naive bayes tends to produce inaccurate predictions when characteristics are not independent given the classlabel. Therefore, it can be concluded that the SVM algorithmis the best ML model for the proposed work. However, the model was subjected to a single dataset and therefore needs further training and testing on the basis of the features selected in the work. From the observed results it can be concluded that the classifiers that worked the best are the ones which could work with well with correlated features setand perform binary classification on them.

A. Data Visualiztions

Thorough data visualizations and data analysis was performed on the dataset to understand and gain insights of the hidden trends and subjects on hand.

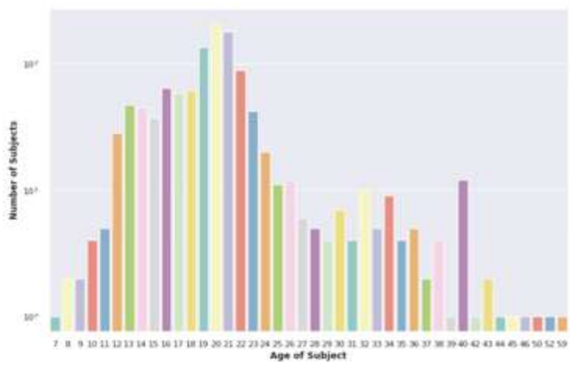

Fig. 3: Age Of Subjects

In the above fig.3, the X - axis represents Age of subject and Y- axis represents Number of Subject considered to perform the analysis during the pandemic**.** The bar graph represents the number of students and their respective age groups who were considered for this analysis. The maximum number of subjects who were considered for the analysis were from theage group 20-21. The minimum number of subjects who were considered for the analysis were from the age groups 7and 44-59.

Fig. 4: Time spent count

In the above figure, the bar plot shows the time spent by the subjects during the pandemic in different tasks like Online Classes, Self-Study, Fitness, Sleep, social media and TV.

It can be inferred that subjects have spent maximum of their time on sleep and minimum of their time on fitness during the pandemic period.

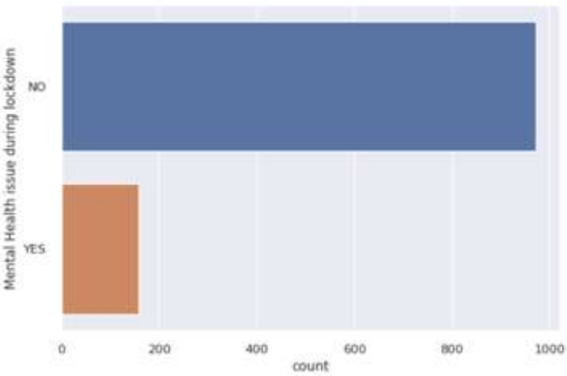

Fig. 5: Mental Health Issue Count

The bar graph above depicts the number of young people afflicted by various mental health disorders during lockdown. It can be shown that around 200 students experienced mental health concerns, whereas most students did not have any mental health problems. Overall, we can observe that most of the participants in the sample did not have any mental health difficulties.

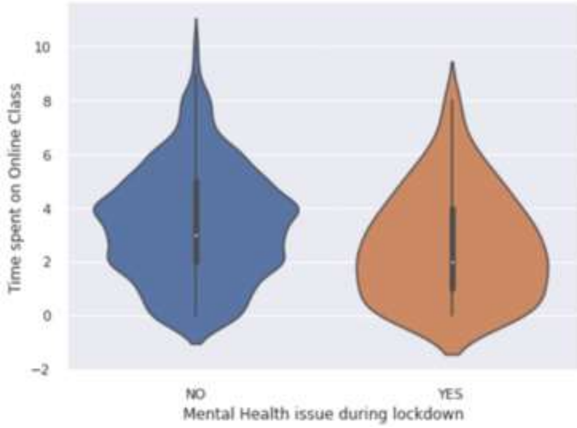

Fig. 6: Mental Health Issue vs Time Spent on Online Class

The violin plot above demonstrates the variation of the number of young people who spent significant study time taking online classes. We divided the graph based on whether the same group of participants experienced any mental health concerns during lockdown. As we can see, theinterquartile range of those who are not experiencing mentalhealth difficulties while taking online classes is higher than the interquartile range of people experiencing mental health issues when taking online classes.

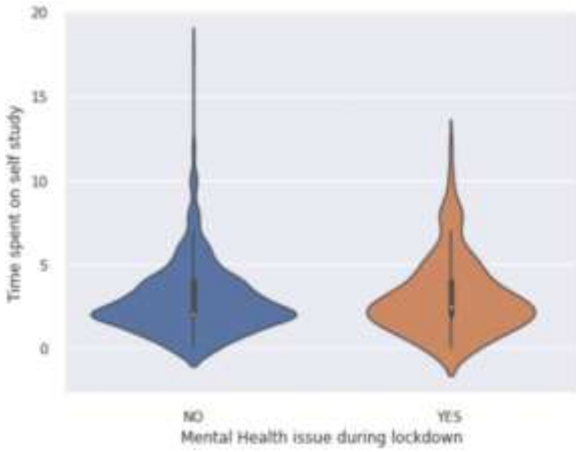

Fig. 7: Mental Health Issue vs Time Spent on Self Study

The violin plot above depicts the distribution of young individuals who spent substantial study time studying independently. The graph was separated based on whether the same set of subjects reported any mental health issues during lockdown. As we can see, the interquartile range of those who are not having mental health challenges and spend most of their time self-studying is almost identical tothe interquartile range of those who are facing mental health issues and spend the majority of their time self-studying. However, there are more outliers among individuals who arenot having mental health challenges and spend time on self- study than among those who are experiencing mental health concerns.

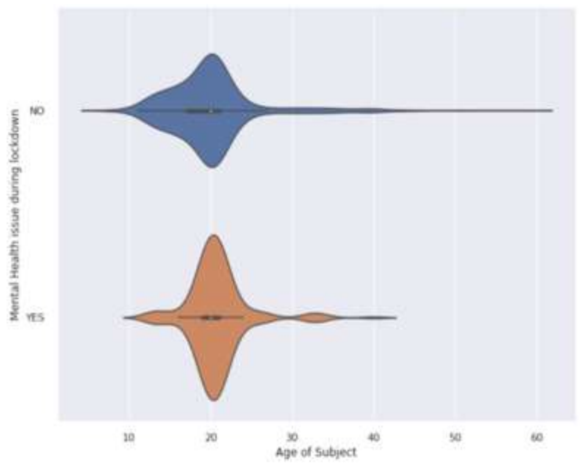

Fig. 8: Age of Subject vs Mental Health Issue

This graph represents the relation between age of the subject and if they had a mental issue during the lockdown. As we can see from the graph, most of the subjects are in their teenage or in their twenties and themedian age is 20 as well. The graph suggests that mostof the people taken in this study seem to have had a mental health problem during the lockdown according to the factors considered.

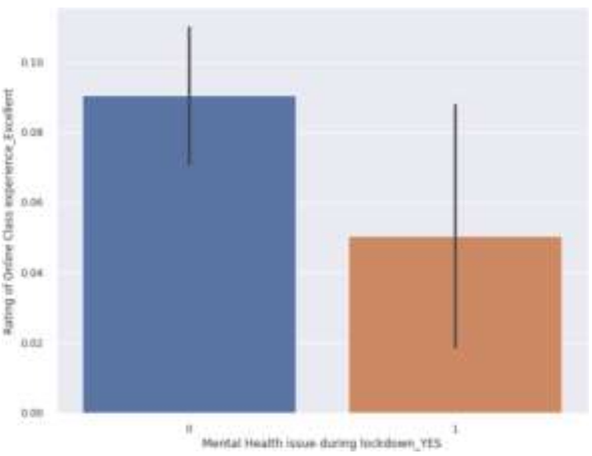

Fig.9: Mental Health Issue vs Online Class Rating

This graph represents the correlation between the experienceof students in online classes and mental health issue. Out of the 1182 students, most of the students who found the online classes to be useful and excellent have not had mental health issues while the students who couldn't cope up with the online classes had to suffer with mental health issues. So,we can infer a negative correlation between opinion towardsonline classes and existence of mental health issue.

VIII.CONCLUSION

Students' stress levels can be accurately predicted using supervised machine learning algorithms by studying the key variables affecting the problem at hand. Data from student surveys on a variety of topics, including time spent studying, social media, health and fitness, etc., provide a solid foundation for this process. A thorough comparison of numerous ML models, including Naive Bayes, Random Forest, Artificial Neural Networks (ANN), etc., has been conducted with the suggestion of the best algorithm forstress level prediction.

The most frequent cause of poor student performance is mental health issues. Mental illness can influence students' motivation, focus, and social connections—all of which are crucial components of their academic success. Numerous universities and colleges around the world have turned to online learning as a result of the recent coronavirus pandemic. Emergency remote learning (ERL) was widely used in higher education during the COVID-19 epidemic,but little is known about the factors that affect student happiness and stress levels in such a novel learning environment.

REFERENCES

NHS press conference, February 4, 2020. Beijing, China. National Health Commission (NHC) of the People's Republic of China.

World Health Organization; Geneva, Switzerland: 2020. WHO: coronavirus disease 2019 (COVID-19) situation report – 23.

Hughes J., Wilson M., Luby S., Gurley E., Hossain M. Transmission of human infection with Nipah virus. Clin Infect Dis. 2009; 49(11):1743–1748.

Burki T.K. Coronavirus in China. Lancet Respir Med. 2020

Al Dhaheri AS, Bataineh MF, Mohamad MN, Ajab A, Al Marzouqi A, et al. (2021) Impact of COVID-19 on mental health and quality of life: Is there any effect? A cross-sectional study of the MENA region.

Dawel A, Shou Y, Smithson M, Cherbuin N, Banfield M, Calear AL, Farrer LM, Gray D, Gulliver A, Housen T, McCallum SM, Morse AR, Murray K, Newman E, Rodney Harris RM and Batterham PJ (2020) The Effect of COVID-19 on Mental Health and Wellbeing in a Representative Sample of Australian Adults. Front. Psychiatry11:579985. doi: 10.3389/fpsyt.2020.579985

Xiong J, Lipsitz O, Nasri F, Lui LMW, Gill H, Phan L, Chen-Li D, Iacobucci M, Ho R, Majeed A, McIntyre RS. Impact of

COVID-19 pandemic on mental health in the general population: A systematic review. J Affect Disord. 2020 Dec 1; 277:55-64. doi: 10.1016/j.jad.2020.08.001. Epub 2020 Aug 8. PMID: 32799105; PMCID: PMC7413844.

Schäfer S, K, Sopp M, R, Schanz C, G, Staginnus M, Göritz A, S, Michael T: Impact of COVID-19 on Public Mental Health and the Buffering Effect of a Sense of Coherence. Psychother Psychosom 2020; 89:386-392. doi: 10.1159/000510752

De Kock, J.H., Latham, H.A., Leslie, S.J. et al. A rapid review of the impact of COVID-19 on the mental health of healthcare workers: implications for supporting psychological well-being. BMC Public Health 21, 104 (2021).https://doi.org/10.1186/s12889-020-10070-3

Son C, Hegde S, Smith A, Wang X, Sasangohar F Effects of COVID-19 on College Students' Mental Health in the United States: Interview Survey Study J Med Internet Res 2020; 22(9):e21279

Michaela C. Pascoe, Sarah E. Hetrick & Alexandra G. Parker (2020) The impact of stress on students in secondary school and highereducation, International Journal of Adolescence and Youth, 25:1, 104- 112, DOI: 10.1080/02673843.2019.1596823

Clabaugh A, Duque JF and Fields LJ (2021) Academic Stress and Emotional Well-Being in United States College Students Following Onset of the COVID-19 Pandemic. Front. Psychol. 12:628787. doi: 10.3389/fpsyg.2021.628787

Yang C, Chen A, Chen Y (2021) College students' stress and health in the COVID-19 pandemic: The role of academic workload, separation from school, and fears of contagion. PLOS ONE 16(2): e0246676. https://doi.org/10.1371/journal.pone.0246676

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Brobbey, Emmanuel. (2021). The impact of stress on the academic performance of students in the University of Cape Coast, School of Business.. Academia Open.

Lee J, Jeong HJ, Kim S. Stress, Anxiety, and Depression Among Undergraduate Students during the COVID-19 Pandemic and their Use of Mental Health Services. Innov High Educ. 2021; 46(5):519- 538. doi: 10.1007/s10755-021-09552-y. Epub 2021 Apr 23. PMID: 33907351; PMCID: PMC8062254.

Yikealo, Dawit & Tareke, Werede & Karvinen, Ikali. (2018). The Level of Stress among College Students: A Case in the College of Education, Eritrea Institute of Technology. Open Science Journal. 3. 10.23954/osj.v3i4.1691.

Malik, M., Javed, S. Perceived stress among university students in Oman during COVID-19-induced e-learning. Middle East Curr Psychiatry 28, 49 (2021). https://doi.org/10.1186/s43045-021-00

Benjet C. Stress management interventions for college students in the context of the COVID-19 pandemic. Clin Psychol (New York). 2020 Jun 16:e12353. doi: 10.1111/cpsp.12353. Epub ahead of print. PMID: 32837028; PMCID: PMC7323064.

Schwartz, Kelly Dean, Deinera Exner-Cortens, Carly A. McMorris, Erica Makarenko, Paul Arnold, Marisa Van Bavel, Sarah Williams, and Rachel Canfield. "COVID-19 and Student Well-Being: Stress and Mental Health during Return-to-School." Canadian Journal of School Psychology 36, no. 2 (June 2021): 166–85.

João Pedro Azevedo, Amer Hasan, Diana Goldemberg, Koen Geven, Syedah Aroob Iqbal, Simulating the Potential Impacts of COVID-19 School Closures on Schooling and Learning Outcomes: A Set of Global Estimates, The World Bank Research Observer, Volume 36, Issue 1, February 2021, Pages 1–40, https://doi.org/10.1093/wbro/lkab003

Engzell, PerFrey, Arun, Verhagen, Mark D. Learning loss due to school closures during the COVID-19 pandemic 2021, Proceedings ofthe National Academy of Sciences, e202237611811817 doi:10.1073/pnas.2022376118

Batra, Kavita, Manoj Sharma, Ravi Batra, Tejinder Pal Singh, and Nena Schvaneveldt. 2021. "Assessing the Psychological Impact of COVID-19 among College Students: An Evidence of 15 Countries" Healthcare 9, no.2:222. https://doi.org/10.3390/healthcare9020222

Marelli, S., Castelnuovo, A., Somma, A. et al. Impact of COVID-19 lockdown on sleep quality in university students and administration staff. J Neurol 268, 8–15 (2021). https://doi.org/10.1007/s00415-020-10056-6

Osea Giuntella, Kelly Hyde, Silvia Saccardo, Sally Sadoff, Lifestyle and mental health disruptions during COVID-19, Journal Article, 2021, Proceedings of the National Academy of Sciences, PMID – 33571107

Ravinder Ahuja, Alisha Banga, Mental Stress Detection in University Students using Machine Learning Algorithms, Procedia Computer Science, Volume 152, 2019, Pages 349-353, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2019.05.007.

Shafiee, Nor & Mutalib, Sofianita. (2020). Prediction of Mental Health Problems among Higher Education Student Using Machine Learning. International Journal of Education and Management Engineering. 10. 1-9. 10.5815/ijeme.2020.06.01.

Parthiban, K., Pandey, D. & Pandey, B.K. Impact of SARS-CoV-2 in Online Education, Predicting and Contrasting Mental Stress of YoungStudents: A Machine Learning Approach. Augment Hum Res 6, 10 (2021). https://doi.org/10.1007/s41133-021-00048-0

Harapan H, Itoh N, Yufika A, Winardi W, Keam S, Te H, Megawati D, Hayati Z, Wagner AL, Mudatsir M. Coronavirus disease 2019 (COVID-19): A literature review. J Infect Public Health. 2020 May; 13(5):667-673. doi: 10.1016/j.jiph.2020.03.019. Epub 2020 Apr 8. PMID: 32340833; PMCID: PMC7142680.

Lu H., Stratton C.W., Tang Y.W. Outbreak of pneumonia of unknown etiology in Wuhan China: the mystery and the miracle. J Med Virol. 2020