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Stress Prediction in Higher Education Students using Psychometric Assessments and AOA-CNN-XGBoost Models

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***Abstract* –Research backs up the common perception that the years preceding up to college are the most difficult, showing that students report higher levels of discomfort and worse self-esteem during this switch. Positive personality qualities such as optimism, hope, and happiness were examined in this system along with 215 first-semester Israeli university students' ratings of functional impairment, psychological distress, and self-esteem. The three stages that make up this suggested method are data preprocessing, model training, and feature selection. In order to process data that would be infeasible to process without data preprocessing, the data can be adjusted to meet the specifications of each data mining technique. Beginning with different forms of feature classification or aggregation and progressing to individual activity levels, several levels of feature granularity were investigated in order to employ a feature selection technique. The proposed approach used an AOA-CNN-XGBoost for the whole model training phase. This novel method outperforms CNN and AOA with an average accuracy of 89.27%.**

***Keywords*—Stress Prediction, Arithmetic Optimization Algorithm (AOA), Educational Psychological Assessment.**

I. INTRODUCTION

The amount of work that students have to accomplish on top of their academics, extracurricular, and jobs nowadays might be overwhelming. A chronically stressful social and academic environment can lead to heart illness, cognitive impairment, immune system suppression, altered brain structure causing memory and cognition disorders, and poor academic performance. Researchers from many universities have worked together to develop a number of stresses detecting technologies. Heart rate variability, skin conductance, cortisol levels, and heart rate are used by a small percentage of the population. One self-reporting tool that does not depend on sensors to ascertain the user's stress levels is the Perceived Stress Scale. Thanks to the emergence of high-quality, robust sensors in wearable's like FitBit, Apple Watch, and telephones, it is now easy and inexpensive to efficiently acquire physiological and behavioral data. The Student Life app on Android smartphones to collect a plethora of data, including but not limited to: activity levels, whereabouts, conversations, sleep patterns, and mental health metrics including stress levels. Among the recognized problems is the lack of clarity around what exactly causes students' mental health troubles. Environmental, psychological, and biological elements can all have an impact. It can be difficult and time-consuming to make a diagnosis, and clinicians sometimes make the wrong diagnosis since certain symptoms and variables are similar. The patient may receive the wrong treatment. This environment may exacerbate the patient's dangerous mental illness and put their emotional and behavioral functioning at risk. Investigating the factors that contribute to impact mental health problems and stress among higher education students is the primary objective of this research system. The proposed system also summarizes the present machine learning applications used to study college students' psychological problems. Their mental health problems may make it hard for them to do things like go about their daily lives or build meaningful connections. Regardless, when confronted with such challenges, first-year College students frequently waver between depending on others and going it alone. Despite their desire to experience new freedoms, the system frequently endure a state of "pseudo independence" because the system are financially and emotionally dependent on their parents. To sum up, the risk of poor mental health is significantly higher among college students than among adults and teenagers. More and more, yoga is becoming acknowledged as a holistic practice that helps alleviate stress and enhance psychological well-being. As a practice with its roots in Indian philosophy, yoga is widely believed to have stress-relieving properties. According to meta-analyses and systematic studies, yoga has several benefits, including relieving stress, anxiety, and depression. Yoga's holistic approach addresses both the psychological and physiological aspects of stress at the same time through the practice of physical postures, breathing exercises, and meditation. Those who made yoga a regular part of their lives reported much lower levels of stress, which may indicate that yoga could help students deal with the pressures of school. The main objective of this study is to utilize ML algorithms to predict the changes in students' stress levels as the system practice the common yoga protocol (CYP), a set of yoga activities approved by the Indian government. This system utilized a control-group experimental design and included various groups to measure aspects such as stress, happiness, depression, anxiety, and sleep.

II. LITERATURE SURVEY

College students experiencing mental and emotional stress through distance learning programs are more likely to engage in risky behaviors such as substance abuse, decreased appetite, sleep disturbances, and anxiety [1]. It is difficult to acquire new material and perform poorly in class when one is under stress, according to research, because this condition affects one's attention, memory, and cognitive capacities. According to [2], this prompted studies on stress in higher education. The author draws the conclusion that this data significantly surpasses prior research in light of the increasing prevalence of test anxiety among college students in the last ten years. [3] In recent years, stress genic variables have become more prevalent, exposing students to a broader array of persistent negative mental-emotional experiences and physiological reactions to unfavorable environmental changes. Health goes beyond physical well-being to include a person's mental, emotional, and social health, as stated by the World Health Organization. [4] Positivity, social connection, self-awareness, and the absence of mental and emotional diseases like melancholy and anxiety are all components of mental health. Ten percent to twenty percent of the world's youth have struggled with a mental health condition at some point in their lives. What's more, these issues are currently the main causes of the rise of psychological barriers, such as those that cause risk-taking or suicide [5]. There has been a dramatic increase in the rates of mental health issues such as depression, anxiety, and stress in recent decades. The emotional and mental well-being of young adults is impacted by anxiety disorders and depression, according to multiple recent studies [6]. Critical indicators of mental health, these symptoms, if unrecognized or mistreated, can lead to grave repercussions. Scientific studies published in the last several decades [7] show that college students in Chile are more likely to suffer from depression and anxiety than the general adult and juvenile population. Furthermore, individuals dealing with depression and anxiety often struggle with academic stress, substance abuse, eating disorders, suicide ideation or behavior, and self-injurious behavior [8]. Academic challenges, financial difficulties, and interpersonal problems are among the potential stresses that college students may encounter [9]. How much stress a person feels may depend on things like how creative the system are and how accurately the system perceive the situation. Every person has their own unique reaction to stress. Research suggests that stress can actually lead to improvements in performance, learning, and development [10]. The present circumstance demands one's coping capacities, which leads to emotional suffering. Many studies have found that high levels of stress are associated with anxiety, depression, and academic difficulties. According to [11], some student demographics may be more prone to stress or face more stressors overall. Compared to domestic students, international students face a number of additional challenges, such as homesickness, discrimination, cultural differences (such as communication and teaching styles), and loneliness [12]. Cultural and language barriers can amplify the already substantial difficulties encountered by international students at university. Consequently, international students may have a higher risk of mental health problems than their domestic counterparts [13]. Despite the fact that studies from English-speaking countries have shown that international students may encounter different emotional, academic, and financial challenges than domestic students, this does not account for every international student. It is unknown how much of an impact loneliness and stress have on college students' mental health. [14] One of the hypothesized variables in this system is stress, which may mediate the relationship between psychological well-being and loneliness. A correlation between students' reported stress and loneliness has been shown in earlier studies. [15] A possible explanation for this could be because students who live alone don't have enough individuals the system can rely on in times of need. This notion is supported by previous research that shows how having a social network of supportive persons can improve one's stress resilience. It's "a specific interaction between an individual and their environment that the individual perceives as putting a strain on or surpassing the resources that the individual has available" [16]. To restate, stress arises when a person perceives their own inadequacy to deal with a demanding and challenging environment. That is, not everyone will experience stress in the same way. [17] A high level of general self-esteem, academic self-efficacy, and other trait-like qualities can help people deal with the stresses of everyday life. Research in developmental psychology has shown that self-regulation and self-control are crucial for behavioral and mental health outcomes across life. [18]found that college students who reported higher levels of stress also reported higher levels of anxiety and depression. Researchers have found conflicting findings when looking at college students' stress levels by gender and socioeconomic background. Research has shown that college students, both male and female, experience higher levels of stress. [19]found that while both men and women reported feeling stressed out, women were more like to talk about things that involved family and social relationships, while men were more likely to talk about things that involved competition. People from lower socioeconomic origins reported more stressful life situations than those from higher socioeconomic backgrounds. [20] Also, shelter-in-place orders messed with families' typical schedules, forcing students to do things the system hadn't planned, like homeschool younger siblings or go food shopping for those in their community who were more likely to get the virus. Students were already under a lot of stress from all these major life events, and the system didn't know when schools would return. [21] College campuses are increasingly places where students are dealing with high levels of stress and psychological discomfort, according to various research. In contrast to temporary stress and challenges that may aid effective learning, high levels of chronic stress are linked to disrupted academic performance, attrition, and failure[22]. Consequently, both the general public and university administrations are interested in seeing how students are adjusting to the major changes caused by the pandemic.

III. Proposed System

Being a stress management strategy, yoga can help students. Despite yoga's widespread acceptance, research on how to predict changes in psychological stress among students is underdeveloped. Finding out how regular yoga practice affected students' psychological stress levels and using machine learning to predict how those levels would change in the future were the main objectives of this system.

A. Data Preprocessing:

The term "data preprocessing for data mining" describes the set of steps taken to prepare data for use in data mining techniques. In the famous Knowledge Discovery from Data procedure, it is one of the most crucial steps[23]. Data from the real world isn't a good place to start when doing data mining because it's usually inaccurate, missing value attributes, irrelevant attributes, or contains only aggregate data; it's also noisy, contains differences in names or codes, inconsistent, and redundant. Figure 1 shows how data preparation can change raw data so it fits the requirements of different data mining techniques, allowing for the study of datasets that would be impossible to analyze without it.

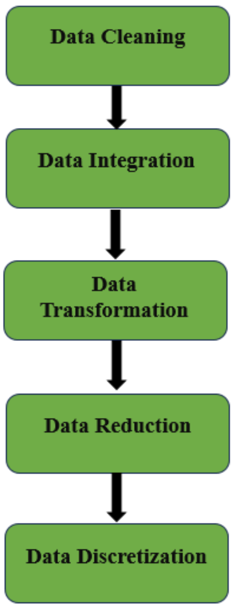

Fig. 1. Data Processing Steps

Also, keep in mind that data collected for academic, industrial, commercial, and scientific purposes is growing at a quick pace and in enormous quantities. Processing ever-increasing data sets requires sophisticated methods. By modifying the data to fit the requirements of each data mining approach, it is possible to process data that would be impossible to handle without data preprocessing. The main components of data preparation are:

1) *Data Cleaning:*

fill in missing values, repair discrepancies, smooth noisy data, and complete the data set by eliminating outliers.

2) *Data Integration:*

using a variety of databases or files.

3) *Data Transformation:*

aggregation and normalization.

4) *Data Reduction:*

while still obtaining similar or same analytical results by reducing the original dataset's attributes.

5) *Data Discretization:*

as part of data reduction, nominal qualities are used instead of numerical ones.

B. Feature Selection:

Data preparation includes operations such as merging and cleansing data, transforming attributes, and reducing or selecting features. By understanding the data, several approaches can be applied to analyze it, with the end goal of uncovering hidden patterns. At this stage, the final dataset is constructed using the initial raw data that was input into the modeling program. Data used in education is often vague, has no practical use, is inconsistent, or has excessive background noise. As a result, throughout this process, it is usual to try to get rid of any unwanted data aspects. To reduce data noise, one can employ binning, regression, or clustering. More than that, there are a variety of approaches to handling missing data. The missing data can be filled in with a global constant or the best guess, or it can be removed entirely. Nevertheless, in each instance, it is necessary to individually investigate the missing values' meanings [24]. Information for this study came from 260 students who participated in the online blended learning course over the course of four years. The results of the interactive lessons were saved using a more standard feature of Moodle, the platform for online education. This rendered the practice of identifying individual students superfluous. Nothing pertaining to the individual's identity was retained. Also exported as application logs were detailed records of their activities. However, this data required cleansing, unlike students' actual grades. The reasoning for this is because these records contained information about administrators, instructors, and other stakeholders, as well as details about activities unrelated to learning. Each student's partial outcomes were combined with the cleaned records. Managing massive amounts of records has long been a significant obstacle for professionals in educational data mining, learning analytics, and educational technology. To get over this problem, research approaches can depend only on logs, which are digital imprints of VLE stakeholders' activity. There should be a significant reduction in the number of unique entries if the input information also contains the kids' grades or accomplishments. The necessity to routinely aggregate data on students' incomplete accomplishments to address problems like data incompleteness, missing values, and the optional nature of student assignments is a typical rationale for this approach. It is not easy to remove the missing values because of their meanings. If students turned in their work but didn't get any points, didn't finish the task, or chose an alternative optional assignment, their answers couldn't be saved. Furthermore, the small size of the dataset makes it impossible to exclude this entry. According to relevant literature reviews in learning analytics and educational data mining, the case study's dataset is sufficient. For prediction models to be accurate and reliable, feature extraction from datasets is essential. This phase is crucial since feature extraction affects the performance of the prediction model directly. In accordance with other studies, different types of inquiries often use different attributes. The digital footprints that students leave behind when the system interact with course materials in an online classroom are a common denominator across all of these issues.

C. Model Training:

1) Deep Neural Networks:

Deep learning methods often find application in the analysis of X-ray pictures. Of all the deep learning models tested, CNN performed the best when it came to classifying X-ray images. By passing the input through several CNN layers and applying narrow filters, the input is transformed. Researchers are focusing on ResNet, ZFNet, AlexNet, GoogLeNet, VGGNet, and LeNet-5 among the many CNN kinds. Because the solution's suggested metaheuristics optimizer is now in the midst of an extensive evolutionary process, large networks can make a substantial computational cost contribution. Overfitting can still happen, especially with very large networks. Because of their simplicity and effectiveness, black and white or grayscale photographs are recommended when working with models like LeNet. The authors propose utilizing a basic network architecture, such LeNet, as the primary classifier to circumvent these limitations and improve real-time processing capabilities. A simplification of the structure would result from this. When it comes to CNNs, the LeNet-5 is at the bottom of the heap. Despite having just two convolutional and one average pooling layer, this network utilizes three fully connected layers for output classification and regression.

2) XGBoost:

The XGBoost algorithm uses an adaptive training technique to optimize objective functions. As a result, each optimization phase is dependent on the previous one. A mathematical representation of the XGBoost model's objective function is provided here:

$$G_k^n = \sum_{o=1}^{i} p\left(w_o, \widehat{w}_o^{n-1} + g_n(v_o)\right) + M(g_n) + T \quad (1)$$

T is the constant term, p is the o -th iteration loss term, and M is the regularization parameter of this model.

$$M(g_n) = \delta(C_n) + \frac{\lambda}{2}\sum_{q=1}^{c} y_q^2 \quad (2)$$

There is usually a clear correlation between the value of the δ and λ customisation selections and the simplicity of the tree structure. Parameter values that are larger suggest a simpler tree structure. Here the proposed approach show the first derivative f and second derivative (z) of the model.

$$f_q = \partial_{\widehat{w}_o^{n-1}} p(w_o, \widehat{w}_o^{n-1}) \quad (3)$$

$$z_q = \partial^2_{\widehat{w}_o^{n-1}} p(w_o, \widehat{w}_o^{n-1}) \quad (4)$$

The solution is obtained using the following formulas:

$$y_q^* = -\frac{\sum f_c}{\sum z_c + \lambda} \quad (5)$$

$$G_k^* = -\frac{1}{2}\sum_{q=1}^{c} \frac{(\sum f)^2}{\sum z + \lambda} + \delta C \quad (6)$$

where G_k^* is the score of the loss function and y_q^* are the weights of the solution.

3) AOA:

A groundbreaking metaheuristic technique called the arithmetic optimization algorithm (AOA) is based on mathematical operators. Starting with V, a randomly generated matrix, AOA optimizes for solutions in the initial optimization space $V_{nq}, 1 \leq n \leq p \; and \; 1 \leq q \leq i$. There is just one answer in this matrix. The best-obtained solution is selected after each iteration and is then considered a candidate for the best solution. Simple arithmetic operations like adding, subtracting, dividing, and multiplying can be used to determine the areas that are near the optimum solution. For both steps, to utilize the Math Optimizer Accelerated (MOA) function to pick the search phase:

$$MOA(c) = Min + c \times \left(\frac{Max - min}{C}\right) \quad (7)$$

where $MOA(c)$ is the value of the c -th iteration function, and the range is from 1 to the maximum iteration number C, where c is the current iteration. Min and Max stand for the lowest and highest values of the accelerated function, respectively. The exploration step involves randomly traversing the search space with the E and R operators for division and multiplication, respectively. Equation (8) expresses this procedure. In the current phase, the search is limited by the MOA when the requirement $m1 > MOA$ is satisfied. In accordance with the first rule of Equation (8), which states that $m2 < 0.6$, the operator (R) will not be utilized until the first operator (E) does its job. If operator (E) is unavailable, the same can be accomplished using the (R) operator.

$$V_{n,q}(c+1) = \begin{cases} best(V_q) \div (MOP + \epsilon) \times (BU_q - PU_q) \times \mu \times PU_q, & m2 \\ best(V_q) \times (MOP) \times (BU_q - PU_q) \times \mu \times PU_q, & o/w \end{cases} \quad (8)$$

the n -th solution of the next iteration is $V_{n,q}(c+1)$, the fixed control parameter is B, and the arbitrary small integer is D .For this iteration, the n -th solution is located at $V_{n,q}(c)$ at position q, and the best solution is at best V_q at position q. The q -th position's conventional lower and upper bounds are $BU_q \; and \; PU_q$, respectively.

$$MOA(c) = 1 - \frac{c^{1/\beta}}{C^{1/\beta}} \tag{9}$$

IV. Result and Discussion

Topics included in this proposed review include educational evaluation, psychological stress during exam season, psychometric methodologies, and measuring scales for students' stress. A student's social support system, stress levels, and mental health were all factors that were examined. Participants were undergraduates at Abai Kazakh National Pedagogical University who were asked to rate their level of stress using a Likert-type scale and a Google form.

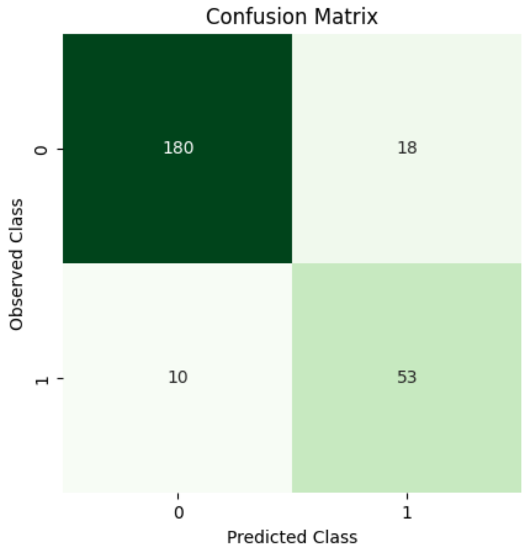

Fig. 2. Confusion Matrix AOA-CNN-XGBoost Model

It is usual practice to utilize the confusion matrix in figure to characterize the accuracy of classification models shown in Figure 2. TP stands for all the instances where the predictions were accurate. All instances where the model's predictions were incorrect are represented by FP. FN stands for instances where the model indicated no stress, but in reality, there is stress, and TN for instances where the model indicated no stress, but in reality, there is no stress either.

TABLE I. PERFORMANCE COMPARISON(%)

Models	Accuracy	Precision	F1-Score	Recall
AOA	0.8535	0.8335	0.8229	0.8425
CNN	0.8705	0.8539	0.8412	0.8642
AOA-CNN-XGBoost	0.8927	0.8746	0.8652	0.8836

The suggested method has the potential to deliver useful findings for stress prediction among college students by use of psychometric assessments. A thorough evaluation was conducted to address this problem; the results are presented in table 1.

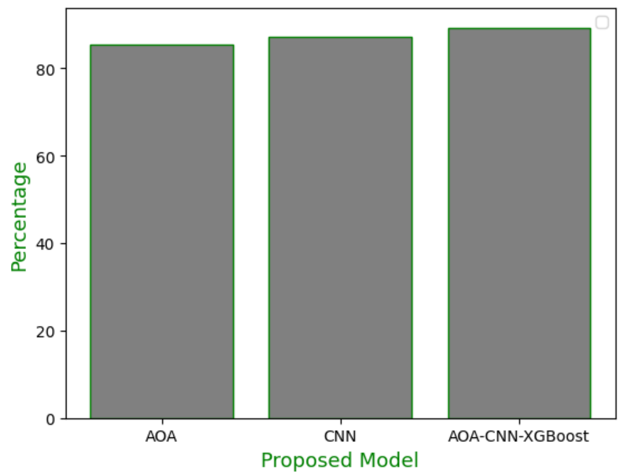

Fig. 3. Graphical Representation of Accuracy Models

With an accuracy of 89.27%, the AOA-CNN-XGBoost achieves the best results. Additionally, CNN has provided us with second-highest accuracy rate, at 87.05%. The outcome is depicted graphically in figure 3.

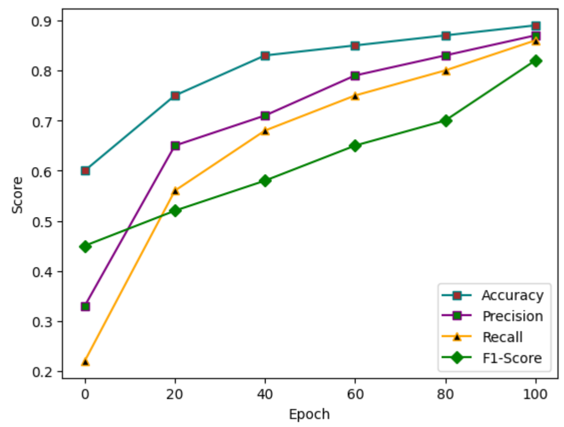

Fig. 4. Proposed Model Epoch per Score

Each proposed model's accuracy loss graph broken down each epoch is displayed in Figure 4. When compared to deep learning, the suggested models are more efficient and produce better results, with low computing time and high accuracy scores.

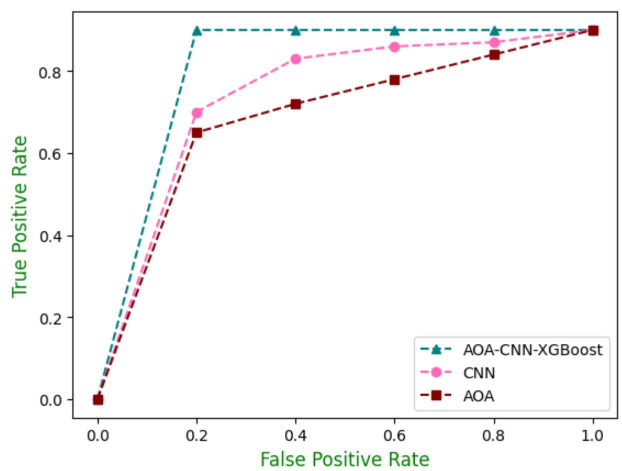

Fig. 5. ROC Curve of the Model

Figure 5 shows the ROC Curve of the model. The ROC curve is a plot that illustrates the performance of a classification model at all possible classification thresholds. It is created by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings.

V. CONCLUSION

University student burnout is a serious problem. Disengaged, unmotivated, and underachieved students may choose to leave the program altogether. The job demand-resource model provides a comprehensive framework for comprehending the factors associated with the development of burnout. There has been less focus on its possible application in the classroom, despite the fact that it has been effective in understanding burnout in the workplace (as shown in multiple studies). By modifying the data to fit the requirements of each data mining approach, it is possible to process data that would be impossible to handle without data preprocessing. The usage of a feature selection technique necessitated investigating a range of feature granularities, beginning with individual activity levels and progressing to various forms of feature classification or aggregation. It was possible to employ only the AOA-CNN-XGBoost model during training. With an average accuracy of 89.27%, the suggested method outperforms AOA and CNN.

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