

Retraction

Retracted: Algorithm for Evaluating the Intervention Effect of Physical Exercise on Stress Groups

Mobile Information Systems

Received 17 October 2023; Accepted 17 October 2023; Published 18 October 2023

Copyright © 2023 Mobile Information Systems. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] B. Yang and Z. Ding, "Algorithm for Evaluating the Intervention Effect of Physical Exercise on Stress Groups," *Mobile Information Systems*, vol. 2022, Article ID 1667814, 9 pages, 2022.

Research Article

Algorithm for Evaluating the Intervention Effect of Physical Exercise on Stress Groups

Bo Yang^{1,2} and Zhizhong Ding³ 

¹School of Sports Economics and Management, Tianjin University of Sport, Tianjin 301617, China

²Sports Department, Tiangong University, Tianjin 300387, China

³School of Economics and Management, Tiangong University, Tianjin 300387, China

Correspondence should be addressed to Zhizhong Ding; dzz@tiangong.edu.cn

Received 12 May 2022; Revised 28 June 2022; Accepted 23 July 2022; Published 18 August 2022

Academic Editor: Mian Ahmad Jan

Copyright © 2022 Bo Yang and Zhizhong Ding. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Mental health is always a concern, especially for students, as they are more prone to stress based on educational burden and competition. Among student groups at different levels, college students are of serious concern as they are an essential pillar of social and economic development, and their mental health has been the society's focus in recent years. With the increasing population leading to the increasing number of college students in our country, the competition for professional learning is also becoming fiercer, seriously affecting students' mental health. Little attention has been paid to adverse effects on mental health or effective mitigation strategies to improve mental health in recent years. However, it is still of grave concern as the stress among students leads to depression, several diseases, and ultimately death. The purpose of this study is to evaluate the effect of physical exercise interventions on stress groups irrespective of their (educational) levels. Physical activity can effectively release stress and is an excellent way to regulate emotions. For this reason, it is a task that the current universities must complete to strengthen physical exercise in students' mental health education. The paper highlights the impact of various social pressures on students' mental health, understands its underlying mechanisms, and explores feasible mitigation strategies for improving and schooling students' mental health. This paper proposes an integrated evaluation-based algorithm to explore the model of the intervention effect of physical exercise on college students. It takes college students as the representative of stress groups. The results show that daily physical activities can effectively relieve the stress of college students.

1. Introduction

Learning stress is the psychological burden and strain induced by highly stimulating the brain and is associated with learning pressure [1]. When students are under moderate learning pressure, they can improve their cognitive abilities and mobilize their initiative and enthusiasm for learning. A good learning process helps students improve their learning efficiency and enhance their skills for a better future. Students under excessive academic pressure are more likely to develop high blood pressure, cardiovascular disease, and cerebrovascular disease, among other physiological problems [2]. They are also more likely to experience negative emotions such as dislike of school, stressing out while

thinking about school, anxiety, depression, and other psychological problems [3]. In severe cases, they are more likely to commit suicide [4]. College students are considered the backbone of a nation's development. Their mental health is always highly concerned for themselves, their parents, and their teachers. They are under increasing amounts of pressure these days due to the rapid development of society leading to high pressure and severe competition. They have many sources of stress such as meeting deadlines, organizing work, maintaining institute and part-time studies, assignments, examinations, and many others. Among all these sources, academic pressure is the most common source of stress and the most common form of psychological stress for college students. According to a study on the social factors

influencing college students majoring in physical education, 60 percent of the students polled stated that academic stress significantly negatively impacted their physical and mental health. Social factors affecting students' physical and mental health include race, class, gender, religion, family, and peer networks.

College can be stressful for many students as they acclimate to their new educational and social environment. It is valid for students who are first-generation college students. International students have an additional task, in this case, different from students going to national-level colleges or universities. They are required to learn other cultural norms and languages in addition to academic preparation [5, 6] and may be under significantly more strain at their universities. Therefore, they face way more pressure than that encountered by other students. As pressures accumulate, an individual's ability to manage or readjust may become overwhelmed, resulting in a depletion of their physical and mental resources. It can lead to a deterioration of mental and physical health, and as a result, the likelihood of medical sickness or psychological suffering due to the stress increases [7]. Numerous studies have examined the influence of stress on college students [8–10]. Despite the enormous amount of data collected and research done on this little subject, the study has been conducted on international students. Several academic pressures are shared by both Chinese and international students, including family related stress, scholarship requirements, financial load, classroom competition, and course-related stress [11]. The individual must battle this stress for the sake of healthy well-being. Individual views of academic stress and coping mechanisms, on the other hand, may differ from one another. As a result, different students may experience and respond to academic stress in various ways.

In this respect, a vast amount of data has been collected in the past few years. According to recent data, college students throughout the country are seeing an increase in stress [12]. The response to any stress may vary based on some factors. Response to a stressor is a state of physical or psychological arousal typically triggered by a stress experience [13]. Additionally, differences in gender perceptions and responses to academic stress are also observed among students. Examples include female students expressing their feelings more. Male students reporting more control over their emotions, accepting issues, disregarding circumstances, and committing to problem-solving [14, 15]. Men are much more stressed than women when the two groups are subjected to similar amounts of stress. A 2016 study in the *Journal of Brain and Behaviour* highlighted that women are twice as likely to suffer from severe stress and anxiety as men when subject to an equal amount of stress [16]. The American Psychological Association supports the statement that the stress gap exists, and those women consistently report higher stress levels than men.

Some of the extreme values for survival in this world nowadays where every individual is exposed to various stressors in his/her everyday life. In this context, mental toughness is an individual's ability to respond to adversity, danger, or other significant stressors. It is also defined as a

protective factor, process, and mechanism that allows individuals to have good performance outcomes when exposed to stressors that harm their psychological development [17]. Mental toughness is related to academic stress and determines the stress coping mechanisms of an individual. Many studies have found that mental toughness is inversely associated with academic stress [18] and that persons with higher mental toughness are more active in coping with stress. Students with high mental resilience are more likely to be proactive in dealing with stress, have better overall academic achievement, and demonstrate good adaptation to stressful situations. Such students are among the least bothered by environmental stressors as they have highly developed stress coping mechanisms. Athletes can bear stress very efficiently as compared to an average person. Researchers have hypothesized that athletes can cope with stress so effectively because more outstanding mental toughness lessens the intensity of perceived stress experienced by athletes.

Physical activity and exertion play a pivotal role in this respect. It can be demonstrated that physical activity can aid in the improvement of an individual's level of mental toughness. One of the most critical ways physical exercises support the mechanism of mental health is through the positive experience that one has while exercising. Mental toughness can be a beneficial exercise experience and can be used to reduce unpleasant feelings efficiently. It has been shown to play a role and mood elevation. Physical activity has been shown to boost mental toughness, and mental toughness improves directly proportional to the intensity of physical activity performed. Mental toughness frequently links stressful conditions and the emotional or behavioral responses of the individuals involved. Therefore, this paper investigates the model of the intervention effect of physical exercise on college students based on data collected from college students' psychological pressure.

The rest of the research paper is organized as follows: Section 2 represents the related work done in this study. Section 3 describes a research design that can be found helpful in relieving the stress. Section 4 sheds light on the results extracted from this study. Finally, Section 4 contains the concluding remarks.

2. Related Work

Various professionals have investigated the science of stress and its effects on the daily life of individuals. Canadian physiologist Hans Selye was one of the first to introduce the notion of stress into the fields of medicine and psychology in the middle of the twentieth century. His studies define stress as a scary incident that causes an individual to become nervous, such as a sudden dangerous stimulus. In the extant literature, there are three primary points of view on what constitutes a stressful situation. In one sense, one refers to the individual's internal state, including the individual's physiological and psychological responses to environmental demands [19, 20]. The second relates to the individual's external environment or event and the load or obligation imposed by the environment on them.

The interaction between individuals and their environment is the subject of the third category. Over time, the definition of stress has been modified. It can be defined in numerous ways. Nowadays, stress is defined as a unique relationship between a person and their environment. The most commonly used by the academic circle of the individual evaluation is the concept of cognitive interaction proposed by Lazarus, which is the most widely accepted definition. When it comes to stress, it is neither a product of the environment nor a reflection of the individual's nature. Instead, it is a relationship between requirements and the ability to meet those wants without going insane or dying. In other words, stress is a unique relationship between people and their environment, which individuals perceive as exceeding their resources and posing a threat to their well-being.

Stress assessment is a favorite topic of many scientists and researchers these days. The goal of stress assessment and measurement [21, 22] is to determine an individual's present level or degree of stress and the type or cause of stress they are experiencing. From the extant literature on stress in the United States and other parts of the world, it can be concluded that the evaluation and measurement of stress are primarily carried out from two perspectives the stress source and the stress reaction. Stress assessment and measurement focus on understanding the internal and external stimuli that cause individuals to become stressed over a specific time, which are referred to as stressors. The measurement and assessment of stress can be performed in many different ways.

Stress can be assessed and measured through observation, interview, questionnaire, or scale. The questionnaire approach is the most often utilized method in research. It involves a list of questions forwarded to a community of people to inquire about stress levels and stress management. When it comes to stress assessment and measurement, a stress-response approach is used, which focuses on understanding the physical and mental responses of individuals to stressful situations or events. Individual stress responses are typically assessed and measured in psychology through situational observations, interviews, and self-reports, to name a few methods. This perspective views individuals and stressors as interconnected, emphasizing understanding the interaction between individuals and stressors. This perspective allows us to evaluate and measure stress with the most remarkable accuracy possible from a dynamic and developmental perspective. The interview and situational assessment methods are more appropriate for this measurement and evaluation [23]. The situational assessment refers to the systematic process involving gathering, analyzing, synthesizing, and communicating data for better planning and decision making.

In most cases, this situational assessment helps make qualitative decisions to achieve defined goals, objectives, target audience, and activities of a health promotion strategy. Therefore, the situational assessment of the students is essential to understand their state of mind and psyche for better guidance and help in decision making. In addition to understanding the stressful situation and the characteristics

of the individual, it can also understand the individual's perception, cognition, and evaluation of the stressful situation and their resources, as well as understanding the stressful situation and their resources. The student should increase his understanding of the coping mechanisms and how the stressful environment alters due to these strategies.

The occurrence or nonoccurrence of a psychological crisis has a significant impact on the subjective factors of an individual. Inadequate self-awareness, thinking habits, personality flaws, and a low ability to cope with setbacks are the internal variables contributing to the psychological crisis experienced by college students. While external variables such as peer pressure and significant psychological crises are essential, the college students themselves are the most crucial aspect to consider when generating psychological stress among college students. The mental illness graph by age is shown in Figure 1.

According to recent research, the current frequency of mental illness among college students [25, 26] is increasing year after year, with the highest prevalence occurring in the first year of college. According to experts, the periods between the first and third years are the most common for depression. First-year students must not only adjust to a new study environment and way of life but also to the strain of competing against their superiors. Third-year students are faced with a slew of new options for preparing for their future development, including postgraduate entrance examinations, employment, and international travel. According to relevant survey data, the mental health status of college students [27–30] is concerning; a significant number of college students experience negative emotions, and more than half of all college students who drop out of school due to mental illness are female. As a result, psychological problems have emerged as a problem that negatively impacts the personal development of college students. Mental health cases concerning suicide or psychologist annually is shown in Figure 2.

A vital aspect of the stability of the school. Because a considerable number of college students suffer from mild to severe psychological difficulties, mental health education for college students must be implemented. Psychological issues in college students are caused by various circumstances, including the stress of studying, falling in love, being far from home, working, and having interpersonal relationships. College students are concerned about not being able to complete their degrees. Students, influenced by their academic environment, leave their homes after joining university and live with a group of strangers in their dorms. Various conflicts will occur due to diverse living practices, resulting in feelings of anxiousness. The employment situation for college students is growing increasingly difficult at the moment. Students will feel befuddled and helpless as a result of their lack of understanding of their majors and future work opportunities. According to studies conducted by several universities, mental illness has risen to the top of the list of reasons college students drop out.

For many years, physical activity has been shown to improve both physical and mental health in individuals effectively. Many researchers stated that physical activity has

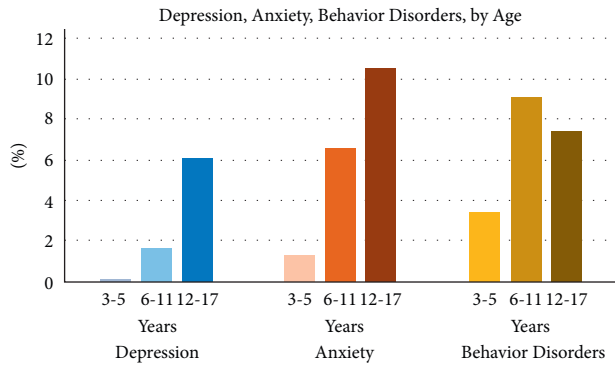


FIGURE 1: Mental illness graph by age [24].

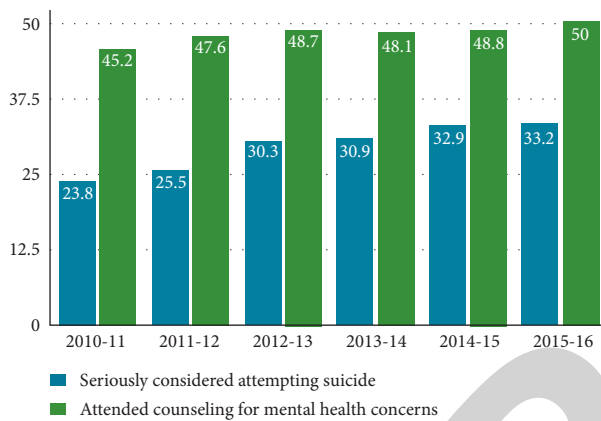


FIGURE 2: Mental health cases concerning suicide or psychologist annually [31].

a considerable potential to enhance well-being. It can include brisk walking, running, jogging, and yoga, for several minutes for a healthy positive energy and a stress-free mind. Healthy sports and food also help in having stable, healthy mental health. It has long been a hot topic in the fields of sports and psychology to figure out how better to boost individual human mental health through physical activity. Physical activity has been found in studies to be beneficial in reducing and treating stress. Regular physical activity, according to the findings of relevant experimental investigations, can reduce the number or sensitivity of adrenergic receptors and heart rate and blood pressure when done regularly. Physical exercise is more effective in helping people recover from extreme stressful events than other methods such as reflection and music enjoyment.

Individual or long-term participation in physical exercise can considerably reduce anxiety, depression, and other destructive emotions brought on by stressful situations. While it can be observed that physical exercise impacts and can alleviate psychological strain, academic pressure is the most common form of psychological pressure for college students, and research on the relationship between physical exercise and academic pressure is limited in scope. Toward this end, this study will conduct an in-depth investigation into the internal relationship between physical exercise and

college students' academic stress, and it will put forward the hypothesis that physical exercise has a negative predictive effect on college students' academic stress and can alleviate the academic stress of college students.

Contradictory findings have emerged from research into the effects of physical activity on mental health. Physical activity is associated with a number of positive health outcomes, including decreased overall mortality [32], improved musculoskeletal fitness and stress regulation, and a decreased risk of cardiovascular disease, obesity, stroke, and cancer [33]. Physical activity is also associated with improved musculoskeletal fitness and stress regulation. Based on the combined effects of randomized controlled clinical trials [34–36] and associations between patients identified in national registry data, most studies conclude that exercise is an effective treatment for mild and moderate depression, either as a stand-alone treatment or in conjunction with other treatments. Although other randomized controlled trials (RCTs) contradict this notion [37], evidence from longitudinal observational studies is equivocal, with favorable relationships shown in adults [38, 39] but not in adolescents. An RCT is a practical implementation of the program or policy's interventions' impact evolution selected randomly for any specific problem. It acts as a control group for the specific slot of the problem. For the most part, the findings of these studies have supported the notion that more physical activity is beneficial, which is supported by the inverse relationship between recreational physical activity and mental health and better results in dose-comparison RCTs for participants who engage in vigorous physical activity.

In some cases, the choice of a minor or unrepresentative sample may contribute to the contradictory results. Because just a few types of exercise are likely to be represented, and only a small number of participants would participate in each type, such studies lack the statistical power to investigate the effects of exercise type. This inability to determine the specificity of this link is further complicated by the lack of a large enough sample size. To put it another way, the relationship between other features of exercise, such as the frequency, intensity, or duration of the exercise, and mental health, as well as how that relationship fluctuates across all potential frequency or duration ranges, is discussed in this paper. Individuals who like a specific exercise can practice that based on their interests and peace of mind. However, all the exercises are of equal importance and have particular objectives. Beyond this, anyone can do any exercise as they do not have preferred advantages over each other, but one can take a prescription by a fitness trainer or a physiologist.

3. Research Design

The introduction and the pieces of literature discussed in Sections 1 and 2 conclude that mental health is a serious problem among students at a very young age. This leads the students to depression and suicide, which is not what should happen to the youth and future of one's country. The researchers called this because of a lack of stress handling

capabilities and physical maintenance. For the lack of stress handling capabilities, one should practice stress handling psychological activities, and for physical maintenance, the exercises and physical consultancy help a lot. This section presents the integrated evolution algorithm for generated data from the survey. This data will be distributed in the train and test section and later examined through the gradient boost decision tree algorithm. The complete design and work of the algorithm are detailed in this section.

3.1. Data Processing. Data processing is a valuable technique for collecting, translating, and analyzing the data to extract required content. The data collected for this work is from a survey conducted among Beijing University students. The collected data are based on parameters such as stress, mental health, physical health, and exercise. The data are organized and distributed in the train and test classes. The training class is always of a higher ratio than the test class as more training data generate a more stable, accurate, and efficient algorithm. The section discusses the data sources and the data class balancing for utilizing the data in a better way.

3.1.1. Data Sources. The data come from a survey of students at a university in Beijing. As part of the physical exercise data, the stress data of the students and the exercise data of the students on a particular APP were obtained by the stress assessment questionnaire, which also served as the physical exercise data.

The primary goal of this study is to develop a predictive model with consistent performance that can be used as an example of an evaluation algorithm for the effect of physical exercise on college students' psychological stress intervention as part of a more extensive study. Three questions have been chosen to serve as the indicator. To begin, a compensation algorithm is utilized to fill up the gaps left by the missing information. Then, an appropriate oversampling strategy is selected to address the problem of class imbalance. Whenever the collected data are not in a suitable amount, the algorithms fail to get proper training. This problem is called the imbalance of class which occurs when the class or classes do not have a sufficient amount of data compared to other competitive classes. This problem can be resolved with predictive modeling that can generate the required data based on a prediction by having the provided data as the model's input. The prediction model used in this paper is SMOTE, as discussed in Section 3.1.2. Figure 3 depicts a block diagram of the algorithm's building blocks.

Figure 3 presents the flowchart of the integrated evaluation algorithm to be followed for better data synthesis. The procedure is to generate a dataset that consists of relevant data (collected from the survey). These data are statistically analyzed and distributed in the train and test sets with a ratio of 3:1, respectively. The train set is used for the training of the algorithm. The ratio of the train set is double concerning the test set as extensive training data set trains the algorithm more effectively. The trained algorithm will be used for the classification of data.

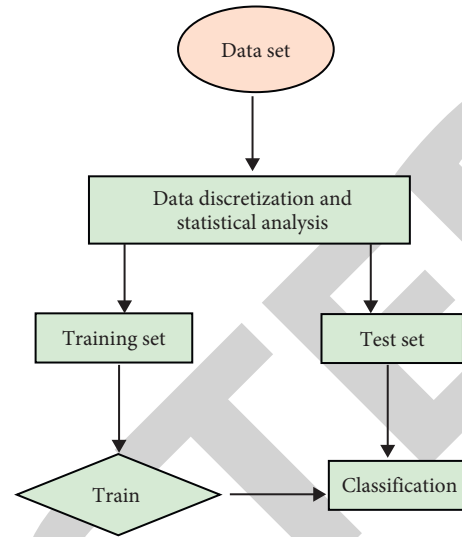


FIGURE 3: Algorithm flowchart.

3.1.2. Data Class Balancing. The Synthetic Minority Over-sampling Technique (SMOTE) of artificially manufactured minority class samples augments the data by randomly producing new instances rather than merely replicating existing samples from the original data. SMOTE is an over-sampling technique used to generate synthetic samples instead of duplicate data samples for the minority class. It is preferred as it enhances the algorithm's performance and reduces the overfitting problems. The performance is enhanced by the less specific and more extensive decision boundaries that help generalize more data resulting in a higher performance rate [40]. It is more effective than other sampling techniques because the SMOTE is employed to address the class imbalance issue. Using a particular minority class sample x , locate the samples that are the closest neighbors to it and other minority class samples, then compute the difference between them. Once this difference is calculated, a random number in the range of 0 to 1 is multiplied and added to the original sample x . Create fresh samples for testing by using the following formula through SMOTE.

$$x_{\text{new}} = x + w\|\hat{x} - x\|, \quad (1)$$

where x indicates the sample of a minority class that has been provided. w denotes random weight, while $0 < w < 1$ denotes the number one. The distance function is represented by the letter $\|\cdot\|$. \hat{x} denotes the nearest neighbor of the integer x . Primarily, it generates a new sample by randomly inserting a point between the two closest minority samples, a procedure known as sample generation.

3.2. Gradient Boost Decision Tree. The Gradient Boost Decision Tree (GBDT) is another excellent ensemble method to be explored further. GBDT is a Machine Learning (ML) algorithm preferably used in regression and classification tasks based on the system's requirements. GBDT employs an iterative method to construct a decision tree and evaluates the model by minimizing the loss function, similar to a

random forest. GBDT is selected over several other algorithms as it offers faster training speed and higher efficiency [41]. While moving in the direction of the gradient descent of the loss function, the GBDT model continuously updates the parameters of the present model, and the model is continuously tuned until the loss function converges to the global minimum.

If $\{x_i, y_i\}_{i=1}^n$ represents the training dataset, $F(x)$ represents the GBDT's prediction model, and $L(y, F(x))$ represents the loss function, then the following equation can be used. The aim function of GBDT is to maximize the prediction model $F(x)$ by identifying the smallest possible value of $L(y, F(x))$ in the prediction. The following process can be used to represent the GBDT training process.

- (1) Set the prediction model $F_0(x)$ to a constant value.

$$F_0(x) = \operatorname{argmin}_{\gamma} \sum_{i=1}^N L(y_i, \gamma). \quad (2)$$

When the decision tree classifier γ is also initialized as a constant, in addition to the decision tree classifier.

- (2) m cycles through the numbers 1 to K . m is the number of times the loop iterates (K is the maximum number of iterations). Each iteration creates a regression tree-based weak classifier and provides the predicted value $F_m(x)$ for the associated observed value. The following is the formula for calculating the negative gradient:

$$-g_k(x) = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)}, \quad (3)$$

$$i = \{1, 2, \dots, N\}.$$

- (3) The regression tree formed by the weak classifier is denoted by $h(x; \alpha_m)$, and the m^{th} regression tree should be established in the direction of the loss function's gradient descent by $m-1$. Because of this, the parameter α_m is changed in the following manner:

$$\alpha_m = \operatorname{argmin}_{\alpha, \beta} \sum_{i=1}^N [-g_k(x) - \beta h(x_i; \alpha)]^2. \quad (4)$$

- (4) Optimize the step size in the direction of gradient descent, which causes the loss function to decrease over the experiment steadily.

$$\beta_m = \operatorname{argmin}_{\beta} L(y_i, F_{m-1}(x_i) + \beta h(x_i; \alpha_m)). \quad (5)$$

- (5) The prediction function of the model is modified in the following ways after each iteration.

$$F_m(x) = F_{m-1}(x) + \beta_m h(x_i; \alpha). \quad (6)$$

The above mathematical equations are to be transformed into the form of an algorithm through proper programming. These mathematical equations will help determine the

correct class at the end of classification. The section is led by the experimental setup discussed in Section 3.3.

3.3. Experimental Setup. Before the experiment, the data were standardized to reduce discrepancies across characteristics and eliminate bias. It is necessary to use a fivefold cross-validation approach in this experiment to acquire consistent and credible results. The necessitated inclusion of additional measures is obtained due to the presence of missing data and class imbalance in the data in this study to evaluate the classification performance thoroughly. As a result, the confusion matrix is concluded, as given in Table 1.

The accuracy of a prediction is defined as the proportion of correctly predicted samples in all of the samples.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \quad (7)$$

Precision is defined as the proportion of samples whose true class is positive among the samples projected to be positive in a given set of circumstances.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \quad (8)$$

The recall rate is the percentage of true positive samples that the model correctly predicts out of the total number of actual positive samples.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \quad (9)$$

The experiment will be performed on the surveyed data using the proposed GBDT algorithm. The confusion matrix will provide the results to determine the system's accuracy and efficiency. Along with this, the GBDT results will be compared with the results of four different ML algorithms to examine the feasibility of the designed algorithm. All the further details are provided in Section 4.

4. Results

To ensure that the strategy described in this work performs as expected at each level, many sets of comparative experiments are designed at each stage. Apart from the GBDT (OUR) method stated in this work, experiments were carried out using the Random Forest (RF) algorithm, the Naive-Bayes (NB) algorithm, the Decision Tree (DT) algorithm, and the Logistic Regression (LR) classification algorithms, amongst each other. Random Forest algorithm is a supervised ML algorithm that can be implemented for classification and regression problems. The RF algorithm works by developing the decision trees and making decisions based on those trees. The NB algorithm is an independent algorithm used to classify different data. The algorithm is designed on the Bayes theorem with an assumption of independence among predictors. The algorithm determines the posterior data based on the prior, likelihood, and evidence data about the class or classes.

The DT algorithm is also a supervised ML algorithm and works similarly to the RF algorithm but is better for

TABLE 1: Confusion matrix.

	True class (positive)	True class (negative)
Predicted class (positive)	TP (true positive)	FP (false positive)
Predictive class (negative)	FN (false negative)	TN (true negative)

regression problems. The most common application of the DT algorithm is data mining. The LR model is a classification and regression model that requires stack, input, output, and parsing tables for data analysis. It is also a supervised learning classification algorithm that performs predictions based on the probability of the targeted data. As shown in Figure 4, five classifiers were employed to categorize the original dataset in this investigation. The results were utilized as a benchmark, as was the case in previous studies. We can see from the results of the original dataset that the accuracy, precision, and recall of the OUR method are not as good as they could have been for that dataset.

On the original dataset, the data preprocessing is executed. On the treated data, the SMOTE method is used to perform class balancing processing on the data, resulting in a new set of processed data. At the end, the RF, NB, DT, LR, and OUR algorithms were used to perform classification prediction on the newly processed dataset using the abovementioned techniques. As shown in Figure 5, we obtain different outcomes. Based on this new dataset, we can observe that the OUR algorithm’s accuracy and precision are the highest of the five categorization prediction algorithms evaluated. The recall rate is below average. This demonstrates that the OUR algorithm is still quite effective for categorizing the effects of physical activity on college students’ stress intervention. The impacts of interventions can be effectively classified. It can be an excellent tool for encouraging college students to engage in physical activity to relieve stress.

The new dataset calculates the receiver operating characteristic ROC value of the OUR method, as shown in Figure 6. It can be observed that the ROC value of the OUR method is exceptionally close to 1, indicating that the algorithm’s performance is still outstanding on the newly processed dataset.

For many years, physical activity has been shown to improve both physical and mental health in individuals effectively. It has long been a hot topic in the fields of sports and psychology to figure out how better to boost individual human mental health through physical activity. Physical activity has been found in studies to be beneficial in reducing and treating stress. Regular physical activity, according to the findings of relevant experimental investigations, can reduce the number or sensitivity of adrenergic receptors and heart rate and blood pressure when done regularly. Physical exercise is more effective in helping people recover from extreme stressful events than other methods such as reflection and music enjoyment. Individual or long-term participation in physical exercise can considerably reduce anxiety, depression, and other bad emotions brought on by stressful situations. While it can be observed that physical

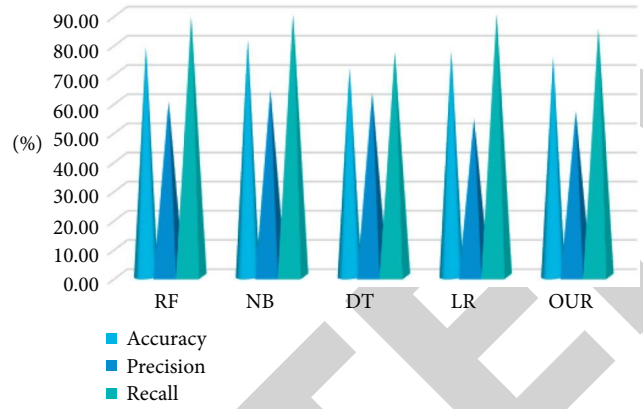


FIGURE 4: Results under raw data.

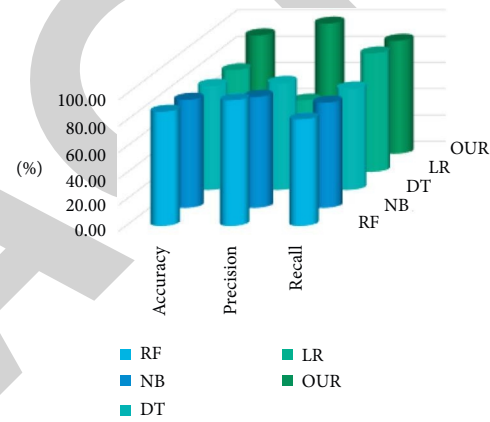


FIGURE 5: Results under processed data.

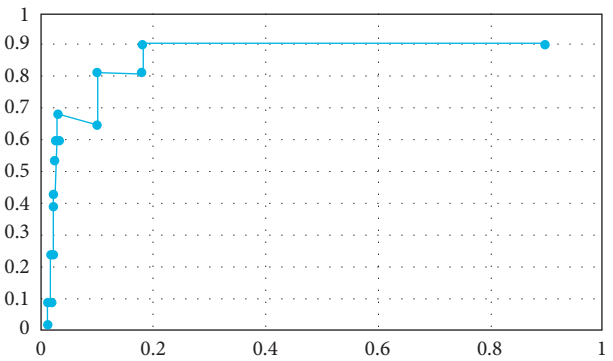


FIGURE 6: ROC value.

exercise impacts and can alleviate psychological strain, academic pressure is the most common form of psychological pressure for college students, and research on the relationship between physical exercise and academic pressure is limited in scope. Accordingly, our research will conduct an in-depth study on the inner link between physical exercise and college students’ academic stress, and we will propose a hypothesis that physical exercise has a negative predictive effect on college students’ academic stress and that physical exercise can help college students relieve their academic stress. The results of our model also support this theory.

5. Conclusion

To improve the accuracy of prediction and early detection of the intervention impact of physical exercise on stress groups, an algorithm is developed that tackles the shortcomings that have been identified in existing prediction models while also employing the mean approach to fill in the gaps. Class imbalance causes various difficulties in classification results, ultimately leading to erroneous findings for the classifier. The SMOTE method is utilized in the model to balance the data. The model of the intervention impact of physical exercise on stress groups was thus created in this manner. Upon further examination, it is discovered that our model exhibits excellent generalization capability. There are ramifications for mental health education in colleges and universities based on the findings of this research. Because there would be more mental health specialists in colleges and universities, they would be able to develop more effective preventive and treatment programs for college students. Some college students may find that cognitive strategies help them manage stress. Some college students may exhibit behavioral responses when faced with a stressful situation. Because of this, mental health professionals must employ a variety of stress-reduction techniques to be effective. Exercise and counseling focusing on constructive behavioral coping skills, such as yoga, will benefit students who demonstrate behavioral reactions. According to the findings, this study presents empirical evidence for a relationship that has been observed and recognized experimentally and culturally for thousands of years.

This work may also have flaws because our dataset contains data from evaluation scales, which may cause some confusion. No formal interviews or standardized rating instruments were used to collect these datasets. As a result, our assessment instruments do not adequately represent students' stress levels in their classes. Furthermore, we are unable to link present stress changes with physical exercise. Therefore, the practical deployment is still not possible, but reliable data can make it possible.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] I. Ud Din, S. Tu, P. Hao et al., "Sequential damage study induced in fiber reinforced composites by shear and tensile stress using a newly developed Arcan fixture," *Journal of Materials Research and Technology*, vol. 9, no. 6, pp. 13352–13364, 2020.
- [2] K. M. Conley and B. J. Lehman, "Test anxiety and cardiovascular responses to daily academic stressors," *Stress and Health*, vol. 28, no. 1, pp. 41–50, 2012.
- [3] A. S. Quach, N. B. Epstein, P. J. Riley, M. K. Falconier, and X. Fang, "Effects of parental warmth and academic pressure on anxiety and depression symptoms in Chinese adolescents," *Journal of Child and Family Studies*, vol. 24, no. 1, pp. 106–116, 2015.
- [4] R. P. Ang and V. S. Huan, "Relationship between academic stress and suicidal ideation: testing for depression as a mediator using multiple regression," *Child Psychiatry and Human Development*, vol. 37, no. 2, pp. 133–143, 2006.
- [5] P. K. Essandoh, "Counseling issues with African college students in US colleges and universities," *The Counseling Psychologist*, vol. 23, no. 2, pp. 348–360, 1995.
- [6] S. C. Mori, "Addressing the mental health concerns of international students," *Journal of Counseling & Development*, vol. 78, no. 2, pp. 137–144, 2000.
- [7] L. I. Pearlin, *Stress and Mental Health: A Conceptual Overview*, Cambridge University Press, Cambridge, UK, 1999.
- [8] K. J. Edwards, P. J. Hershberger, R. K. Russell, and R. J. Markert, "Stress, negative social exchange, and health symptoms in university students," *Journal of American College Health*, vol. 50, no. 2, pp. 75–79, 2001.
- [9] E. A. Pierceall and M. C. Keim, "Stress and coping strategies among community college students," *Community College Journal of Research and Practice*, vol. 31, no. 9, pp. 703–712, 2007.
- [10] A. Reifman and C. Dunkel-Schetter, "Stress, structural social support, and well-being in university students," *Journal of American College Health*, vol. 38, no. 6, pp. 271–277, 1990.
- [11] E. C. Chang, "Cultural differences in psychological distress in Asian and Caucasian American college students: examining the role of cognitive and affective concomitants," *Journal of Counseling Psychology*, vol. 49, no. 1, pp. 47–59, 2002.
- [12] P. A. Thoits, "Stress, coping, and social support processes: where are we? What next?" *Journal of Health and Social Behavior*, vol. 35, pp. 53–79, 1995.
- [13] J. S. Hyde and E. A. Plant, *Magnitude of Psychological Gender Differences: Another Side to the story*, American Psychological Association, Washington, DC, USA, 1995.
- [14] R. Misra and L. G. Castillo, "Academic stress among college students: comparison of American and international students," *International Journal of Stress Management*, vol. 11, no. 2, pp. 132–148, 2004.
- [15] O. Remes, C. Brayne, R. Van Der Linde, and L. Lafortune, "A systematic review of reviews on the Prevalence of anxiety disorders in adult populations," *Brain and Behavior*, vol. 6, no. 7, Article ID e00497, 2016.
- [16] G. E. Richardson, "The metatheory of resilience and resiliency," *Journal of Clinical Psychology*, vol. 58, no. 3, pp. 307–321, 2002.
- [17] K. W. Back, "The mediating effects of hope between participation in school physical education, academic stress, ego-resilience and psychological well-being in high school students," *Indian Journal of Science and Technology*, vol. 8, no. S7, p. 603, 2015.
- [18] K. W. Griffin, R. Friend, P. Eitel, and M. Lobel, "Effects of environmental demands, stress, and mood on health practices," *Journal of Behavioral Medicine*, vol. 16, no. 6, pp. 643–661, 1993.
- [19] J. C. Vischer, "The effects of the physical environment on job performance: towards a theoretical model of workspace stress," *Stress and Health*, vol. 23, no. 3, pp. 175–184, 2007.
- [20] F. Al-Shargie, M. Kiguchi, N. Badruddin, S. C. Dass, A. F. M. Hani, and T. B. Tang, "Mental stress assessment using

- simultaneous measurement of EEG and fNIRS,” *Biomedical Optics Express*, vol. 7, no. 10, pp. 3882–3898, 2016.
- [21] F. R. D. Alfano, B. I. Palella, and G. Riccio, “The role of measurement accuracy on the heat stress assessment according to ISO 7933: 2004,” *Environ. Toxicol.*, vol. 11, pp. 115–124, 2007.
- [22] J. Huang, “An Internet of Things Evaluation Algorithm for Quality Assessment of Computer-Based Teaching,” *Mobile Information Systems*, vol. 2021, Article ID 9919399, 10 pages, 2021.
- [23] P. J. Withers, M. Turski, L. Edwards, P. J. Bouchard, and D. J. Buttle, “Recent advances in residual stress measurement,” *International Journal of Pressure Vessels and Piping*, vol. 85, no. 3, pp. 118–127, 2008.
- [24] Center of Disease Control and Prevention, “Data and Statistics on Children’s Mental Health,” *Center of Disease Control and Prevention Retrieved September*, vol. 13, 2022.
- [25] J. C. Quick, “Introduction to the measurement of stress at work,” *Journal of Occupational Health Psychology*, vol. 3, no. 4, pp. 291–293, 1998.
- [26] M. R. Rashmi, B. M. Shweta, T. Agrawal, F. N. Fathima, M. N. Ghiya, and B. Thomas, “Prevalence of Probable Mental Illness Among College Students in a Select university in Bangalore Rural District,” vol. 73, 2014.
- [27] P. Pedrelli, M. Nyer, A. Yeung, C. Zulauf, and T. Wilens, “College students: mental health problems and treatment considerations,” *Academic Psychiatry*, vol. 39, no. 5, pp. 503–511, 2015.
- [28] M. A. Kitzrow, “The mental health needs of today’s college students: challenges and recommendations,” *NASPA Journal*, vol. 41, no. 1, pp. 167–181, 2003.
- [29] L. J. Cook, “Striving to help college students with mental health issues,” *Journal of Psychosocial Nursing and Mental Health Services*, vol. 45, no. 4, pp. 40–44, 2007.
- [30] J. B. Yorgason, D. Linville, and B. Zitzman, “Mental health among college students: do those who need services know about and use them?” *Journal of American College Health*, vol. 57, no. 2, pp. 173–182, 2008.
- [31] The Echo, “Growing need of mental health help in universities,” 2018, <https://cluecho.com/9653/uncategorized/growing-need-mental-health-help-universities/>.
- [32] I. M. Lee, E. J. Shiroma, F. Lobelo, P. Puska, S. N. Blair, and P. T. Katzmarzyk, “Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy,” *The Lancet*, vol. 380, no. 9838, pp. 219–229, 2012.
- [33] M. P. Herring, P. J. O’Connor, and R. K. Dishman, “The effect of exercise training on anxiety symptoms among patients: a systematic review,” *Archives of Internal Medicine*, vol. 170, no. 4, p. 321, 2010.
- [34] G. M. Cooney, K. Dwan, C. A. Greig et al., “Exercise for depression,” *The Cochrane Database of Systematic Reviews*, vol. 9, Article ID CD004366, 2013.
- [35] S. Kvam, C. L. Kleppe, I. H. Nordhus, and A. Hovland, “Exercise as a treatment for depression: a meta-analysis,” *Journal of Affective Disorders*, vol. 202, pp. 67–86, 2016.
- [36] F. B. Schuch, D. Vancampfort, J. Richards, S. Rosenbaum, P. B. Ward, and B. Stubbs, “Exercise as a treatment for depression: a meta-analysis adjusting for publication bias,” *Journal of Psychiatric Research*, vol. 77, pp. 42–51, 2016.
- [37] M. Chalder, N. J. Wiles, J. Campbell et al., “Facilitated physical activity as a treatment for depressed adults: randomised controlled trial,” *Bmj Clinical Research*, vol. 344, no. jun06 1, p. e2758, 2012.
- [38] S. B. Harvey, S. Øverland, S. L. Hatch, S. Wessely, A. Mykletun, and M. Hotopf, “Exercise and the prevention of depression: results of the HUNT cohort study,” *American Journal of Psychiatry*, vol. 175, no. 1, pp. 28–36, 2018.
- [39] F. B. Schuch, D. Vancampfort, J. Firth et al., “Physical activity and incident depression: a meta-analysis of prospective cohort studies,” *American Journal of Psychiatry*, vol. 175, no. 7, pp. 631–648, 2018.
- [40] Q. Wang, Z. Luo, J. Huang, Y. Feng, and Z. Liu, “A Novel Ensemble Method for Imbalanced Data Learning: Bagging of Extrapolation-SMOTE SVM,” *Computational intelligence and neuroscience*, vol. 2017, Article ID 1827016, 11 pages, 2017.
- [41] G. Yu, S. Zhang, M. Hu, and Y. K. Wang, “Prediction of highway tunnel pavement performance based on digital twin and multiple time series stacking,” *Advances in Civil Engineering*, vol. 2020, Article ID 8824135, 21 pages, 2020.