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Improving Student Wellness by Predicting Stress and Designing Coping Mechanisms with Decision Tree Algorithm

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Abstract. This study adopts a mixed-methods approach integrating different demographic groups to understand and manage the stress levels of students. It attempts to pinpoint student stresses, analyse coping mechanisms, and gauge how well they work for various populations. In order to obtain information, the study uses questionnaires and statistical analysis. Based on the results, it provides helpful advice and coping strategies. It aims to educate academic institutions and mental health professionals leading to targeted interventions that support students academic success and overall wellbeing. The aim of this study is to ascertain students stress levels and assess how well coping strategies work to lower stress. The main biological reasons for the stress are the release of a high level of hormone called cortisol produced by the adrenal glands. Several strategies like having adequate sleep, healthy diet and regular exercises will help to manage the stress. The study will detect avoidance coping among students who live alone and will make the case that knowledge of coping mechanisms is critical to efficient stress management.

Keywords: Coping, effectiveness, positive correlations, well-being

1. Introduction

In the current demanding and fast-paced educational environment students well-being has become a critical concern. With the pressures of academic success combined with personal and social challenges students often feel more stressed out than they used to. The establishment of a secure and productive learning environment depends on the recognition and management of this stress. In this paper a novel approach to enhancing student well-being through stress prediction and coping mechanism customization using advanced machine learning techniques specifically the Decision Tree algorithm is investigated. Studies have shown that stress-related issues are on the rise among students and are negatively affecting their mental and physical well-being as well as their overall quality of life.

Even while they are useful, traditional stress-reduction techniques frequently fail to meet the particular requirements of various student populations. A viable approach is the use of machine learning, which gives individualised insights and solutions predicated on unique data. This problem is especially well suited for the Decision Tree method, which is well-known for its interpretability and capacity to handle complex, non-linear interactions. The program can estimate stress levels precisely and recommend customised coping strategies by examining a variety of parameters, including personal habits, social support, and the burden associated with academics.

In addition to improving the accuracy of stress management interventions, this data-driven strategy gives students practical information that they may use to better navigate their academic journey. This article explores the process of using the Decision Tree algorithm to predict stress levels in students, including how to collect data, preprocess it, choose features, and evaluate the model. We also talk about how our research might be applied practically, providing a thorough framework for academic institutions and mental health practitioners to put in place focused support networks. Finally, the goal of this research is to help build a more helpful and well-balanced learning environment where kids can succeed intellectually and personally.

2. Literature Review

Al-Khalwadeh (2023) [1] investigated coping strategies among students, focusing on Amir Khan's third model. David J. Emerson (2023) [2] used structural equation modeling to explore the relationship between psychological distress, academic burnout, and student burnout among business students. 1,119 from four American universities. Findings suggest that increasing capacity can reduce student turnover and have implications for career readiness and future interventions.

Mehjabeen Khan (2023) [3] examined associations between scholastic self-efficacy, stress-coping aptitudes, and scholastic execution in 66 undergrad understudies. Positive relationships were found between self-efficacy, successful adapting aptitudes, and scholarly execution, proposing the significance of these components in college success. Ashraf Alam and Atasi Mohanty [4] centered on utilizing machine learning methods to foresee understudy victory and recognized at-risk understudies early. By leveraging instructive information mining, their approach pointed to make strides regulation viability and understudy results.

Manjunath. C (2022) [5] proposed a machine learning-based framework to anticipate and oversee understudy stretch levels. Utilizing calculations like Naïve Bayes and KNN, the framework pointed to offer personalized back and counsel to understudies, tending to person stressors and improving generally well-being. Smith, Johnson et. al. (2022) [6] investigated the forecast of understudy stretch levels utilizing machine learning calculations like Back Vector Machines and Irregular Woodland. Whereas recognizing confinements, their ponder offers experiences into components impacting stretch and potential mediations.

Lavinia McLean, David Gaul, Rebecca Penco (2022) [7] inspected social support's part in moderating stretch among first-year college understudies, noticing sex contrasts in recognition and encounter. They advocate for gender-specific activities to improve social bolster frameworks and back understudies amid college transitions.Shivani Mittal et. al. (2022) [8] tended to stretch administration, especially within the setting of the COVID-19 widespread, utilizing administered and unsupervised machine learning calculations. Their approach pointed to raise mindfulness and illuminate policymakers almost compelling stretch administration procedures.

3. Research Methodology

The approach employs surveys for gathering detailed information regarding academic success of students, personal behavior patterns as well as the amount of nervous tension experienced. All the survey responses will be carefully noted down in a dedicated database to ensure that there is proper arrangement and protection of data. During data preprocessing step, incomplete or inconsistent answers will be removed from the dataset and numerical features will be normalized if necessary. Significant variables will be extracted to improve fitness of this dataset for analysis. Expertise from psychology or education would come in handy here in finding major causes of stress levels making it easier for feature selection. Decision Tree algorithm which can be easily explained was chosen to predict stress levels with model training and evaluation carrying out on training and testing sets split out from the dataset. Performance will be evaluated using different metrics such as precision, recall, F1-score, accuracy; cross-validation technique employed to assure consistency. User feedback through survey responses and usability testing provides insights into model's accuracy and practicality while pilot testing with small sample size refines the model based on participant feedbacks. To keep increasing the accuracy and relevance of this model, iterative improvement must go on. The methodology, findings, and recommendations for educators, administrators, and mental health professionals will all be summarized in the comprehensive documentation and reporting.

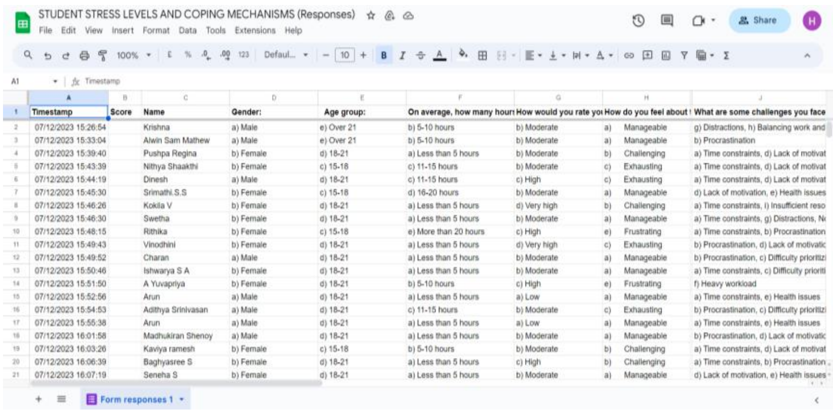
3.1 Data Collection

The dataset from the survey gives an overall picture of different elements of stress, wellbeing and academic experiences on individual basis. It has critical dimensions that start with demographic information such as sex and age group. There is a detailed analysis of academic engagement by focusing on the number of hours spent in studying per week which reveals study habits being used. Stress levels are meticulously assessed involving overall stress levels within an academic year and subjective feelings about workload and expectations. A nuanced exploration of coping mechanisms is achieved through inquiries into feeling overwhelmed, challenges faced in balancing academic responsibilities, and how often they feel stressed up or anxious during examination period. The external pressures including peer pressure, family expectations, and financial strain are analyzed to determine their effect on overall well-being.

The data is made richer with personal and behavioral factors by self-rating how well one manages his/her time, the significance of relationship issues in increasing stress levels, and the frequency of stresses caused by health concerns. Introducing open-ended question invites the participants to add extra stress-causing factors as it adds a qualitative aspect to quantitative data.The dataset parameters include categorical variables, multiple selections, and text responses which provides a nuanced view of academic stress complexities. This enables the researcher to establish patterns that would empower educators and mental health specialists among others to come up with targeted support systems and interventions.

This dataset can be used for training machine learning models on how to predict stress using different input features. This predictive model could help in early intervention efforts as well as tailoring support strategies for people who at high risk of having severe stress. An example could be an application that supplies personalized coping mechanisms, resources and assistance grounded on individuals' own sense of pressure.

The dataset meant for improving student well-being, consisting of 502 samples, can be a significant source of academic research and practical applications like machine learning models or adaptive support apps. The dataset is large enough to investigate the causes of student tension in-depth and develop focused action plans for promoting their well-being. This implies that the data set has a good representation which allows one to conduct complex analysis as seen from figure 1 with insights from 502 respondents.


STUDENT STRESS LEVELS AND COPING MECHANISMS (Responses)

	Timestamp	Score	Name	Gender:	Age group:	On average, how many hour	How would you rate yo	How do you feel about	What are some challenges you face
2	07/12/2023 15:26:54		Krishna	a) Male	e) Over 21	b) 5-10 hours	b) Moderate	a) Manageable	g) Distractions, h) Balancing work and
3	07/12/2023 15:33:04		Alwin Sam Mathew	a) Male	e) Over 21	b) 5-10 hours	b) Moderate	a) Manageable	b) Procrastination
4	07/12/2023 15:39:40		Pushpa Regina	b) Female	d) 18-21	a) Less than 5 hours	b) Moderate	b) Challenging	a) Time constraints, d) Lack of motivat
5	07/12/2023 15:43:39		Nithya Shaakthi	b) Female	c) 15-18	c) 11-15 hours	b) Moderate	c) Exhausting	a) Time constraints, d) Lack of motivat
6	07/12/2023 15:44:19		Dinesh	a) Male	d) 18-21	c) 11-15 hours	c) High	c) Exhausting	a) Time constraints, d) Lack of motivat
7	07/12/2023 15:45:30		Srimathi.S.S	b) Female	c) 15-18	d) 16-20 hours	b) Moderate	a) Manageable	d) Lack of motivation, e) Health issues
8	07/12/2023 15:46:26		Kokila V	b) Female	d) 18-21	a) Less than 5 hours	d) Very high	b) Challenging	a) Time constraints, i) Insufficient reso
9	07/12/2023 15:46:30		Swetha	b) Female	d) 18-21	a) Less than 5 hours	b) Moderate	a) Manageable	a) Time constraints, g) Distractions, N
10	07/12/2023 15:48:15		Rithika	b) Female	c) 15-18	e) More than 20 hours	c) High	e) Frustrating	a) Time constraints, b) Procrastination
11	07/12/2023 15:49:43		Vinodhini	b) Female	d) 18-21	a) Less than 5 hours	d) Very high	c) Exhausting	b) Procrastination, d) Lack of motivatic
12	07/12/2023 15:49:52		Charan	a) Male	d) 18-21	a) Less than 5 hours	b) Moderate	a) Manageable	b) Procrastination, c) Difficulty prioritiz
13	07/12/2023 15:50:46		Ishwarya S A	b) Female	d) 18-21	a) Less than 5 hours	b) Moderate	a) Manageable	a) Time constraints, c) Difficulty prioriti
14	07/12/2023 15:51:50		A Yuvapriya	b) Female	d) 18-21	b) 5-10 hours	c) High	e) Frustrating	f) Heavy workload
15	07/12/2023 15:52:56		Arun	a) Male	d) 18-21	a) Less than 5 hours	a) Low	a) Manageable	a) Time constraints, e) Health issues
16	07/12/2023 15:54:53		Adithya Srinivasan	a) Male	d) 18-21	c) 11-15 hours	b) Moderate	c) Exhausting	b) Procrastination, c) Difficulty prioritiz
17	07/12/2023 15:55:38		Arun	a) Male	d) 18-21	a) Less than 5 hours	a) Low	a) Manageable	a) Time constraints, e) Health issues
18	07/12/2023 16:01:58		Madhukiran Shenoy	a) Male	d) 18-21	a) Less than 5 hours	b) Moderate	a) Manageable	b) Procrastination, d) Lack of motivatic
19	07/12/2023 16:03:26		Kaviya ramesh	b) Female	c) 15-18	b) 5-10 hours	b) Moderate	b) Challenging	a) Time constraints, d) Lack of motivat
20	07/12/2023 16:06:39		Baghyasree S	b) Female	d) 18-21	a) Less than 5 hours	c) High	b) Challenging	a) Time constraints, b) Procrastination
21	07/12/2023 16:07:19		Seneha S	b) Female	d) 18-21	a) Less than 5 hours	b) Moderate	a) Manageable	d) Lack of motivation, e) Health issues

Form responses 1

Fig. 1: Sample Data - Responses from the survey

3.2 Data Preprocessing

For example, the code does such things as cleaning out messes in data and performing preparatory data tasks including handling missing values, mapping categorical values to numeric representations, dropping unnecessary columns as given in figure 2.

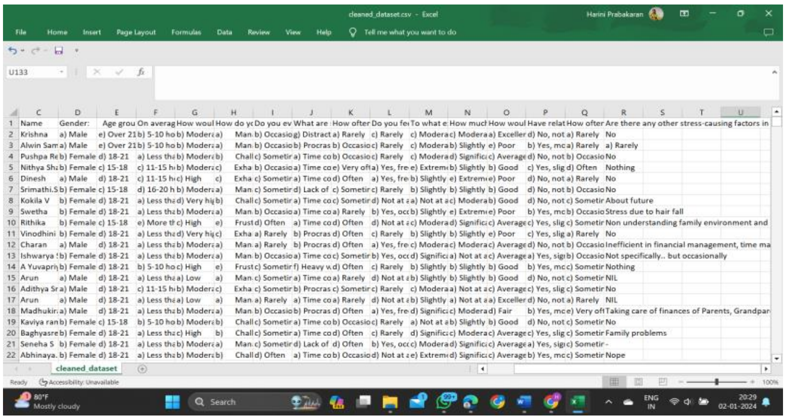


Fig. 2: Preprocessed Dataset

4. Results & Discussions

Consequently, it achieved an impressive accuracy of 96.75% on training dataset while predicting stress levels among students throughout the academic year using decision tree model demonstrations. A minimum number of false positives and negatives are indicated by confusion matrix analysis, which shows how well the model correctly assigns stress levels. It also offers high precision recall and F1-scores across stress level categories according to classification report indicating reliability of this model.

The model's prediction provides useful suggestions for individuals to effectively deal with pressure related anxieties, allowing them to have knowledge-based decisions concerning their lifestyle and coping mechanisms. The decision tree visualization in figure 3 and the graph that demonstrates how predicted stress levels vary offer a simple and intuitive explanation of the model's functionality in terms of both making a decision and performance, thereby enabling understanding and potential improvement for better forecast accuracy.

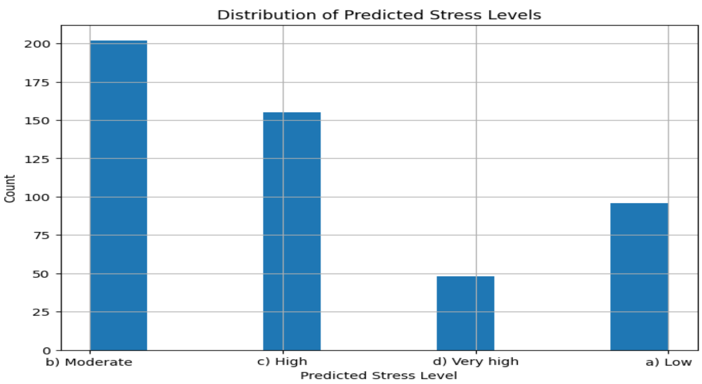


Fig. 3: Distribution of Predicted Stress Levels

5. Conclusion

In summary, this study has shown that the Decision Tree Classifier developed herein can accurately predict academic stress among students based on survey data. High accuracy rates achieved by the model, detailed performance measurements as well as inputs derived from confusion matrix and classification report underscore its high ability to recognize students who are at risk of facing higher level of stresses. This research enables teachers and mental health experts to intervene early enough providing targeted assistance towards encouraging wellness as well as educational achievement amongst students. Moreover, moving forward could entail an exploratory feature importance analysis for determining influential factors while incorporating user feedback in order to make adjustments based upon real-world experience and changing needs.

6. References

[1] Alkhawaldeh, A., Al Omari, O., Al Aldawi, S., Al Hashmi, I., Ann Ballad, C., Ibrahim, A., ... & ALBashtawy, M. (2023). Stress Factors, Stress Levels, and Coping Mechanisms among University Students. The Scientific World Journal, 2023.

[2] Emerson, D. J., Hair Jr, J. F., & Smith, K. J. (2023). Psychological distress, burnout, and business student turnover: The role of resilience as a coping mechanism. Research in higher education, 64(2), 228-259.

[3] Khan, Mehjabeen (2023) "Academic Self-Efficacy, Coping, and Academic Performance in College," International Journal of Undergraduate Research and Creative Activities: Vol. 5: Iss. 1, Article 3.

[4] Alam, A., & Mohanty, A. (2023). Cultural beliefs and equity in educational institutions: exploring the social and philosophical notions of ability groupings in teaching and learning of mathematics. *International Journal of Adolescence and Youth*, *28*(1), 2270662.

[5] Gupta, S., Kaur, N., Kant, K., Jindal, P., Ali, A., & Naeem, M. (2023). Calcium: A master regulator of stress tolerance in plants. *South African Journal of Botany*, *163*, 580-594.

[6] Smith, T. E., Thompson, A. M., & Maynard, B. R. (2022). Self-management interventions for reducing challenging behaviors among school-age students: A systematic review. *Campbell Systematic Reviews*, *18*(1), e1223.

[7] McLean, L., Gaul, D., & Penco, R. (2023). Perceived social support and stress: A study of 1st year students in Ireland. *International Journal of Mental Health and Addiction*, *21*(4), 2101-2121.

[8] Mittal, S., Mahendra, S., Sanap, V., & Churi, P. (2022). How can machine learning be used in stress management: A systematic literature review of applications in workplaces and education. *International Journal of Information Management Data Insights*, *2*(2), 100110.