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An Analytical Study on Academic Pressure and Other Contributors of Student Stress

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Abstract
These days students stress levels became a major problem. Heavy study workload, sleep habits and lifestyle habits have become a major reason, if not properly managed it can lead to serious health problems and effects on understanding abilities in the students. To study patterns, we have taken a student stress dataset having both physiological and behavioral indicators. We have employed statistical analysis, principal component analysis, correlation mapping. Random Forest and XG Boost is used to identify main contributing factors. XG Boost performed well with 95% accuracy. The result shows that academic workload, sleep habits and lifestyle choices significantly effects stress levels. Among These reports suggest data driven approach for stress monitoring and suggest interposition points for education institutions.

Keywords: *Student Stress, Random Forest, XG Boost, Principal Component Analysis, Correlation*

1. Introduction
Nowadays, the Stress in students has become a rising issue in this competitive world. Students experience stress due to various factors, including academic demands, personal problems, social issues, performance targets, examination pressure, financial difficulties, and career expectations. A small amount of pressure will help students to achieve their goals, but prolonged pressure can impact their mental and physical health and, in turn, their academic performance. Unhealthy eating habits sleep patterns and not having proper time management often make the situation poor and it leads to chronic disorders like stomach cancer and Seizures. In this month, one of the students expired because of this reason I have started analyzing Stress management of the student. Understanding the reasons and stress management strategies of student's stress is crucial to create an encouraging learning atmosphere and help students to maintain well-balanced personal and academic lives. Parents, teachers and college play a key role in providing a positive environment where the students can come and express their problems and find support. Yoga lessons and time management and stress management workshops can help them feel less stressed. The main objective of this study is

- To analyse distribution of stress among the students
- To study the correlation between their physical and behavioural factors
- Dimension reductions and classification done through the principal component analysis method

Lastly, Machine Learning Models like Random Forest, XG Boost methods are used to predict the strongest reason for their stress.

2. Literature Review
Student stress is widespread in higher education and has risen over the last decade, with more than

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three-quarters reporting moderate or high stress and frequent academic impairment [1, 2]. Foundational and contemporary work shows study workload and assessment pressure—grades, heavy homework, term papers, and exams—are principal stressors, best understood through transactional appraisal and Job Demands–Resources frameworks that balance demands with coping/resources [4, 15, 18, 22]. Sleeping habits are a central correlate: evidence maps and meta-analyses reveal high prevalence of poor sleep and clear links to electronic media—especially in-bed smartphone use—which undermines sleep quality [6, 11, 14, 20]. Lifestyle behaviors also matter: better diet quality consistently relates to lower depression/anxiety [17, 23, 24], structured physical activity reduces stress and anxiety [7, 8, 12, 13], while excessive caffeine/energy-drink use can aggravate distress—particularly among students who overstudy [16, 21]. Validated measures and moderators guide analysis and intervention: The Perceived Stress Scale captures perceived overload, uncontrollability, and unpredictability [9], and social support can buffer stress effects [10]. Finally, mindfulness / stress-management programs show reliable, moderate benefits—including reductions in test anxiety—while burnout-focused reviews call for pairing individual skills with structural changes to assessment load and course design [3, 5, 19, 25].

3. Data & Methodology

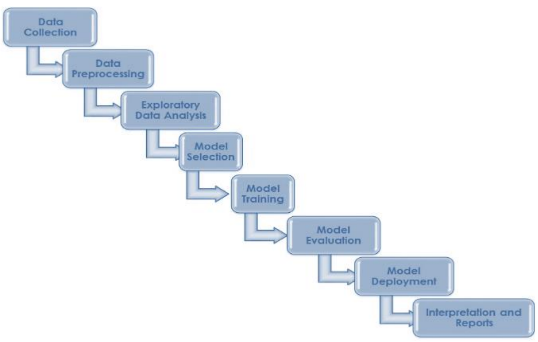

Figure 1 Research Paper Framework

The dataset is taken from Kaggle, and it has 843 rows and 26 columns, and most of the columns are rated on a Likert scale (1-5), where a large number means strong symptoms. The target variable is "Which type of stress do you primarily experience? Spyder 5.1.1 is used for mining data experiments. The Figure 1 Shows framework of the paper, before starting the analysis, the data was cleaned for further analysis. The missing values were filled with the mean of their column. Qualitative responses were cleaned and encoded for further analysis. The numbers were standardized so that they were on the same scale. Once data preprocessing was done, descriptive statistics were used to see how the stress among the students was distributed. Correlation analysis as shown in was done to identify different factors like sleep, workload and health issues. To understand the data easily, the PCA dimension reduction method is used. This method reduces many factors into two main factors and helps us to see student groups with the same stress patterns. Finally, the Random Forest and XG Boost approaches are used to determine which variables were most crucial in stress prediction.

Table 1 Classification Report of Random Forest

Class Label	Precision	Recall	F1-Score	Support
1	0.62	0.33	0.43	15
2	0.52	0.55	0.53	44
3	0.47	0.64	0.54	53
4	0.46	0.41	0.43	39
5	0.5	0.22	0.31	18
Overall Accuracy			**0.49**	**169**
Macro Average	**0.52**	**0.43**	**0.45**	**169**
Weighted Average	**0.5**	**0.49**	**0.48**	**169**

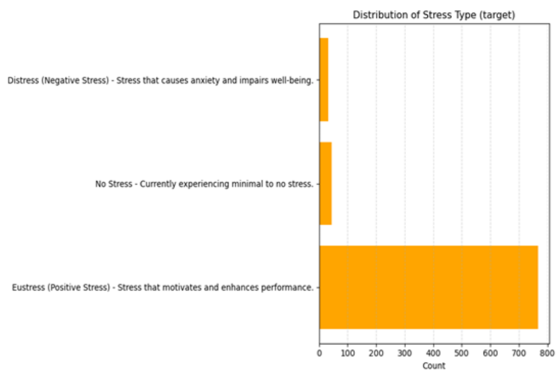

Figure 2 Distribution of Framework

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Table 2 Classification Report of XG Boost

Stress Category	Precision	Recall	F1-Score	Support
Distress (Negative Stress) – Stress that causes anxiety and impairs well-being	1	0.83	0.91	6
Eustress (Positive Stress) – Stress that motivates and enhances performance	0.95	1	0.97	154
No Stress – Minimal or no current stress	1	0.22	0.36	9
Overall Accuracy			**0.95**	**169**
Macro Average	**0.98**	**0.69**	**0.75**	**169**
Weighted Average	**0.96**	**0.95**	**0.94**	**169**

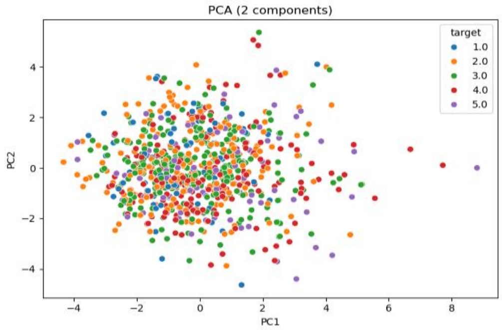

Figure 3 PCA

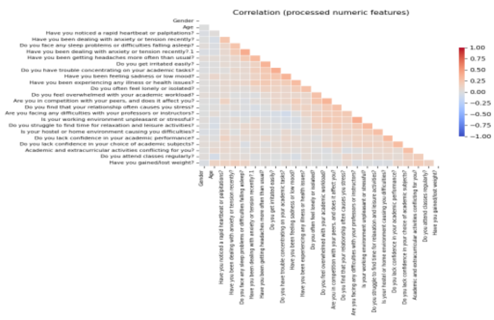

Figure 4 Correlation Map

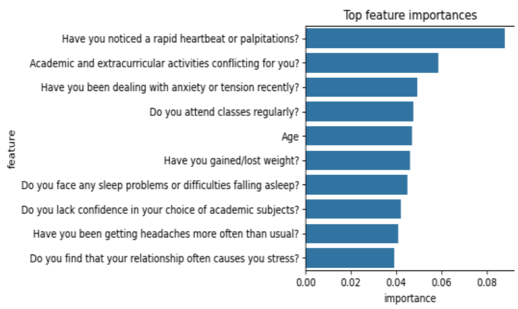

Figure 5 Top Feature Importance

4. Results and Discussion

4.1. Results

The analysis shows that most students reported medium to high stress, the main reason being academic workload. The correlation analysis shows that students who slept less or had irregular sleep patterns experienced more stress, while poor concentration and heavy workload were firmly linked to higher stress. The PCA results as shown in Figure2. helped us group students with similar stress patterns, show that stress is not random but follows plain patterns based on life style and habits. The random forest model as shown in Table1. evidence that the primary factors of stress are lifestyle choices, workload, and sleep quality. The model also performed well in forecasting stress levels; this proves that these features can be used for early detection of stress among students, see student groups with the same stress patterns. Finally, the Random Forest and XG Boost approaches are used to determine which variables were most crucial in stress prediction.

5. Discussion

The results show that study workload, sleep habits and lifestyle habits play a major role in predicting stress in students. The dimension reduction method called PCA in Figure3. shows that students can be clubbed into the same groups depending upon their stress level. Correlation data in Figure4. show how closely groups are related to one another. Machine learning models such as Random Forest and XG Boost were applied to classify students into different levels of stress. The Random Forest model as shown in Table1. produced a moderate accuracy of around 49%, and its F1-scores for the individual classes varied between 0.31 and 0.54. Its performance was noticeably influenced by the imbalance in the dataset, as the model tended to favor the majority class, which resulted in poor recall for the less-represented categories such as Class 1 and Class 5. On the other hand, the XG Boost model as shown in Table2. performed exceptionally well, reaching an overall accuracy of 95%. XG Boost was able to recognize the dominant "Eustress" category with very high precision and recall, and it also performed well in identifying students experiencing "Distress." However, like the Random Forest model, it struggled with the minority "No Stress" group. Its recall for this class was only 0.22, showing that many of these students were misclassified as belonging to the Eustress group. Overall, while Random Forest provides a basic reference point, XG Boost demonstrates far better classification performance. Even so, both models highlight the need to address the imbalance in the dataset to improve predictions for the smaller stress categories. Figure 5 shows Top Feature Importance

Conclusion

Understanding stress in students requires both statistical analysis and modern machine-learning methods. The patterns observed in this study show that factors such as sleep routines, study workload, and daily habits greatly influence students' stress levels. These insights can help educational institutions make practical changes, such as adjusting academic schedules and offering timely counselling support. Future studies that include a larger and more diverse group of students will make the findings stronger and allow the prediction models to work more accurately.

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