Measuring the Impact of Meditation on Academic Stress Levels in UG Students using Machine Learning Models

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Abstract. This study uses machine learning and causal inference techniques to investigate how meditation helps college students who are experiencing academic stress. In order predict stress reduction based on initial psychological responses and demographic characteristics, we examined data from more than 680 students. To classify stress levels and forecast post-meditation outcomes, three machine learning algorithms were evaluated: Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). With 88.24% accuracy, 89.05% precision, and 88.24% recall, the Random Forest model outperformed the others. Accuracy values for KNN and SVM were 77.21% and 63.97%, respectively. The best indicators of stress reduction were age, meditation frequency, and baseline stress. The treated group experienced a significant reduction in stress, particularly among those with medium baseline stress, according to causal analysis (Causal Forest and T-Learner). These results were validated by K-Means clustering, which was consistent with the machine learning outcomes. In conclusion, machine learning models, especially Random Forest, are capable of predicting individual results, and meditation successfully lowers academic stress in specialized circumstances. By combining causal and predictive methods, the study offers insights for developing customized mental health interventions in academic settings.

Keywords: Machine Learning, Meditation, Academic Stress, Mindfulness, Stress Management,

1 Introduction

Due to the demands of coursework, societal expectations, and financial limitations, academic stress has grown to be a serious issue in higher education. Students' emotional and cognitive health may be negatively impacted by these stressors, which could result in anxiety, burnout, and subpar academic performance. Continuous stress is detrimental to mental health and academic performance because it impairs motivation, focus, and learning. Therefore, stress-reduction techniques that support academic achievement and personal growth are highly valued by colleges [2, 7].

Stress management has been found to benefit from meditation, particularly Mindfulness-Based Stress Reduction (MBSR) techniques. Meditation has been shown to improve emotional regulation, lower anxiety, and improve cognitive abilities like memory and focus [1, 4–6]. Meditation is a practical, non-invasive way to improve mental toughness because it strengthens the areas of the brain that control emotions, according to neuroscientific research [1, 5, 12].

However, a large portion of the current meditation research is based on small sample sizes or self-reports, which could result in biased results [2, 13]. A more unbiased, data-driven approach to examining the impact of meditation on stress is machine learning (ML). Based on behavioral and physiological data, machine learning models can categorize students into low, medium, and high stress groups, allowing for more precise stress assessments and customized interventions [3,7,8]. We can more accurately predict stress and customize meditation techniques by integrating machine learning.

2 Literature Review

Numerous interventions have been used to study the effects of academic stress, which has been extensively documented in relation to university students. Yoga, meditation, and mindfulness are among the methods that have demonstrated promise in lowering stress, improving emotional health, and improving focus [1, 4,5]. These practices are beneficial for mental health in higher education because they assist students in developing resilience, managing their emotions, and overcoming academic pressures [19].

Regular meditation practice reduces stress levels in the body and mind, according to the findings of numerous studies on the subject. It improves cognitive function, memory, and motivation, all of which are important for academic success [4, 10]. Furthermore, meditation improves students' wellbeing, reduces burnout, and fosters emotional control [11].

So Hum and Anapanasati are two meditation techniques that help people sleep better and reduce stress, which enhances their academic performance [9–12]. Recent developments that integrate machine learning (ML) and mindfulness research have made it possible to predict stress and provide tailored interventions. By evaluating behavioral and physiological data, machine learning optimizes online mindfulness programs and boosts their efficacy [7, 8, 13, 14].

Even with these developments, there are still unanswered questions about the long-term impacts of meditation and the ideal circumstances for its efficacy. Although ML has a lot of promise for tailoring interventions, more investigation is required to improve these techniques and address biases in existing research. [3, 18].

Future research is made more exciting by these gaps, especially when it comes to combining clinical, behavioral, and computational methods to enhance stress-reduction tactics in higher education.

3 Methodology

3.1 Research Design

This cross-sectional, quantitative study investigated the effects of meditation on college students' academic stress. Links between demographics, meditation practices, and stress levels were investigated using machine learning models, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest, K-Means Clustering, and Causal Forest.

3.2 Sample and Participants

Students between the ages of 14 and 25 who were enrolled in programs like BCA, B.Com, B.Sc., MCA, and M.Sc. provided a total of 680 valid responses. Fair representation across disciplines was guaranteed by simple random sampling. 71.5% of the participants meditated, as opposed to 28.5% who did not. The study complied with ethical research guidelines, and each participant provided informed consent.

3.3 Data Collection Procedure

A structured, self-administered questionnaire was used to collect data on the following topics:

– **Demographics:** age, gender, semester, academic program.
– **Meditation Practices:** type, frequency, and duration.
– **Academic Stress:** Likert-scale items on time constraints, performance anxiety, task management, and general stress.
– **Physical Symptoms:** headaches, fatigue, insomnia, and muscle tension.

Outliers were eliminated, categorical variables were encoded, and continuous variables were normalized using Min–Max scaling. 680 observations with stress levels classified as low, medium, or high before and after the intervention made up the final dataset.

3.4 Feature engineering and preprocessing

Preprocessing and feature engineering procedures were used prior to feeding the data into machine learning models:

– **Data Cleaning**: Mean imputation for continuous variables and mode imputation for categorical variables were used to impute missing values. The Z-score method was used to identify outliers:

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

where X is the observed value, μ is the mean, and σ is the standard deviation.

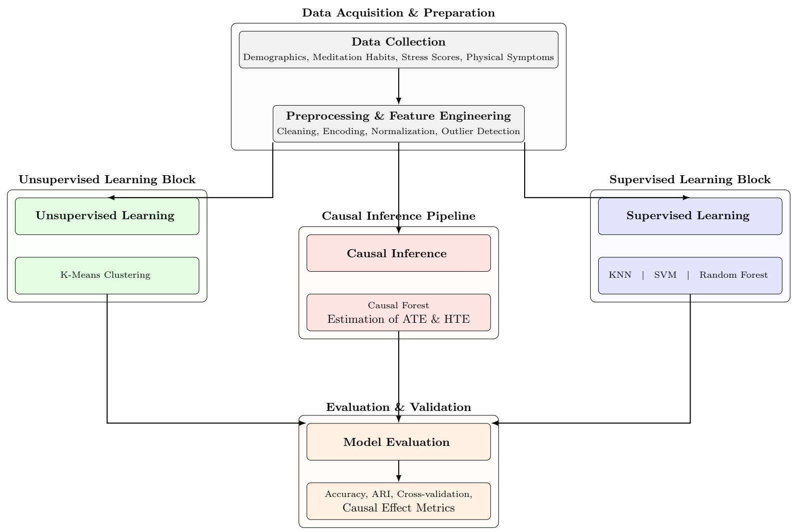


Fig. 1: Overview of Data Processing and Learning Pipeline.

– **Feature Encoding**: For model compatibility, one-hot encoding was used to encode categorical features like gender and type of meditation.
– **Normalization**: Using Min-Max scaling, continuous features such as age and stress levels were normalized to the range ([0, 1]):

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

3.5 Ethical Considerations

To ensure confidentiality, all participant data was anonymized and processed in compliance with stringent privacy guidelines. Every participant gave their informed consent, and no AI systems were given access to personal data.

3.6 Intervention Procedure

Certified human instructors led guided breath-based and mindfulness meditation sessions for the intervention group. Sessions lasted five to fifteen minutes each and were held one to three times a week for six weeks. During the sessions, no artificial intelligence or digital tools were utilized.

4 Machine Learning Models

Several kinds of machine learning models were used to investigate the relationship between meditation and academic stress. The K-Nearest Neighbors (KNN) algorithm classifies data points based on the majority class of their closest neighbors. To divide stress levels into three groups—high, medium, and low—Support Vector Machines (SVM) determines the optimal separating boundary. The Random Forest model is a group of decision trees that decreases overfitting and boosts accuracy through aggregated predictions. Finally, K-Means Clustering is an unsupervised method for clustering related data points by lowering within-cluster variance.

5 Causal Inference Using Causal Forest

Causal Forest is one machine learning method for determining the heterogeneous treatment effects (HTE) in observational data. It proves that meditation and stress are causally related by building a forest of decision trees to forecast each person's treatment outcome.

$$\text{Causal Effect} = E[Y(1) - Y(0)|X] \tag{3}$$

where X stands for individual coefficients and $Y(1)$ and $Y(0)$ for the results of meditation and non-meditation, respectively. Individual variations in the effects of treatment can be controlled with Causal Forest.

6 Evaluation Metrics

The model's performance was assessed using the relevant metrics (accuracy, precision, recall, and F-1 score) for each type of learning: supervised (KNN, SVM, Random Forest), unsupervised (K-Means), and causal inference (Causal Forest). These evaluations ensured robustness and interpretability across models.

6.1 Classification Metrics

We used standard classification metrics from the confusion matrix for supervised models (KNN, SVM, Random Forest), including accuracy, precision, recall, and F1-score. These metrics were used to assess precision to recall ratio, false positive rate, and predictive accuracy. The F1-score is especially helpful for datasets that are not balanced.

To guarantee consistency and uniform class distribution, we used **10-fold stratified cross-validation** for model evaluation.

6.2 Clustering Metrics

Several internal validation metrics were used to evaluate cluster quality for the K-Means Clustering algorithm:

Silhouette Score: Evaluates a data point's similarity to its own cluster in comparison to other clusters:

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{4}$$

where $b(i)$ is the mean nearest-cluster distance and $a(i)$ is the mean intra-cluster distance. Better-defined clusters are indicated by a higher Silhouette Score.

Calinski-Harabasz Index (CHI): Determines the between-cluster dispersion to within-cluster dispersion ratio:

$$CHI = \frac{SSB/(K-1)}{SSW/(n-K)} \tag{5}$$

More distinct and well-separated clusters are indicated by higher CHI values.

Davies-Bouldin Index (DBI): Measures how similar clusters are on average:

$$DBI = \frac{1}{K} \sum_{i=1}^{K} \max_{i \neq j} \left(\frac{\sigma_i + \sigma_j}{d(\mu_i, \mu_j)} \right) \tag{6}$$

where the average distance between a cluster's centroid (mu_i) and its points ($sigma_i$) is represented. Better clustering is indicated by lower DBI values.

6.3 Causal Inference Metrics

The evaluation of the Causal Forest model was focused on determining the treatment effects at the individual and population levels:

Average Treatment Effect (ATE): Calculates the mean difference in results between the treatment and control groups:

$$ATE = \mathbb{E}[Y(1) - Y(0)] \tag{7}$$

Conditional Average Treatment Effect (CATE): Indicates/Represents the expected effect of treatment based on specific control variables:

$$CATE(X) = \mathbb{E}[Y(1) - Y(0) \mid X] \tag{8}$$

Policy Risk: Measures how well the assigned treatment policies are working. More successful policies are indicated by lower policy risk values:

$$R(\pi) = \mathbb{E}[Y(0) + \pi(X) \times (Y(1) - Y(0))] \tag{9}$$

7 Results and Discussion

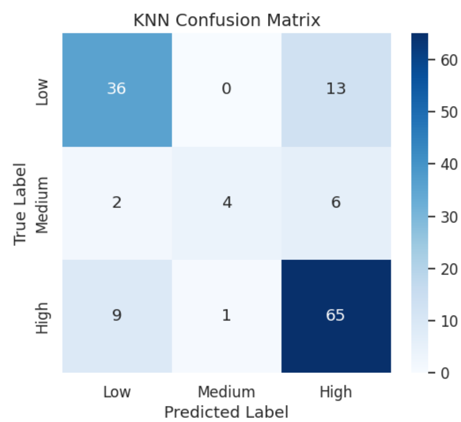
7.1 K-Nearest Neighbors (KNN) Classification

The KNN classifier ($k = 5$) performed moderately well, achieving a test accuracy of 77.21%. Figure 2(b) displays the confusion matrix, which shows that the High stress group was well identified (recall = 0.87), whereas the Low stress group was less correctly identified (recall = 0.73). As shown in Table 2(a), the model performed worst in the Medium stress category, achieving a recall of only 33%. Given that feature distributions overlap more at moderate stress levels, this performance implies that KNN's dependence on proximity in feature space is ineffective for differentiating between high and low extremes.

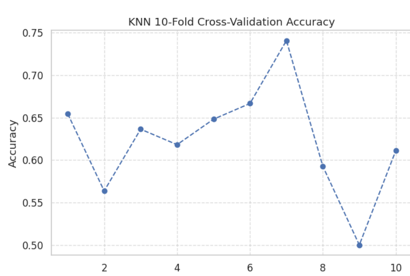
Key performance indicators pointing to an imbalance in the model's capacity to identify each stress category are macro average precision (0.78) and recall (0.64). Although there is variability in detecting different stress levels, the model's weighted F1-score of 0.76 suggests that it is reasonably reliable. Because KNN relies on distance metrics, the model is sensitive to changes in feature scaling and sampling, as evidenced by the 10-fold cross-validation mean accuracy of 0.6232 ($\pm$0.0611) in Figure 2(c).

Metric	Low	Medium	High
Precision	0.77	0.80	0.77
Recall	0.73	0.33	0.87
F1-score	0.75	0.47	0.82

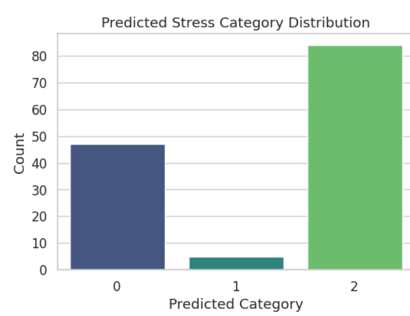
((a)) KNN Classification Metrics



((b)) Confusion Matrix for KNN



((c)) 10 Fold Cross Validation for KNN



((d)) Predicted Stress Category Distribution for KNN

Fig. 2: KNN Model Results: Classification Metrics, Confusion Matrix, Cross Validation, and Predicted Stress Category Distribution.

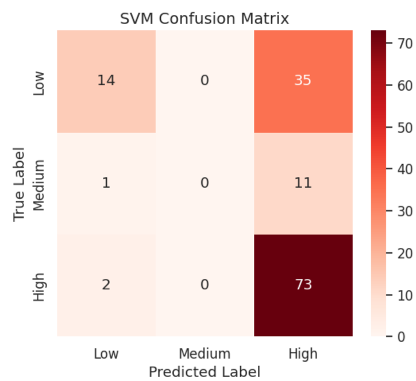
7.2 Support Vector Machine (SVM) Classification

The accuracy of the SVM model with an RBF kernel was 63.97%, which was less than that of Random Forest and KNN. As seen in 3(b), it did well in predicting High stress (recall = 0.97), but it was unable to detect Medium stress at all (recall = 0.00). Low stress recall was likewise low (0.29), and many Low stress cases were incorrectly classified as High stress (Table 3(a)). On the other hand, the precision for low stress was high (0.82), suggesting that it was accurate when expected.

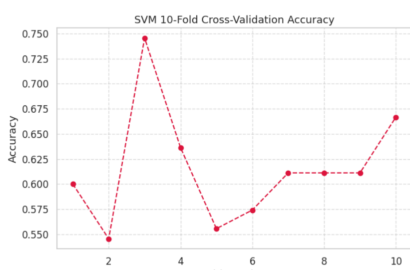
The model's difficulties with non-High categories are demonstrated by the macro average recall (0.42) and F1-score (0.39). Results from cross-validation (mean = 0.6157 ± 0.0552) indicate consistent but subpar performance, pointing to underlying flaws rather than chance (Figure 3(c)).

Metric	**Low**	**Medium**	**High**
Precision	0.82	0.00	0.61
Recall	0.29	0.00	0.97
F1-score	0.42	0.00	0.75

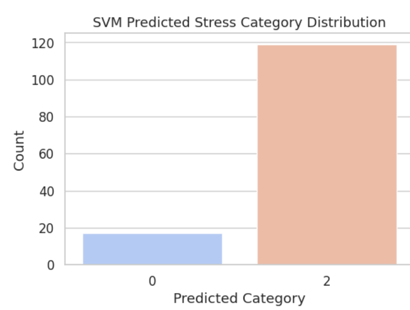
((a)) SVM Classification Metrics



((b)) Confusion Matrix for SVM



((c)) 10 Fold Cross Validation on Accuracy for SVM



((d)) Predicted Stress Category Distribution for SVM

Fig. 3: SVM Model Performance: Classification Metrics, Confusion Matrix, Cross Validation, and Predicted Stress Category Distribution.

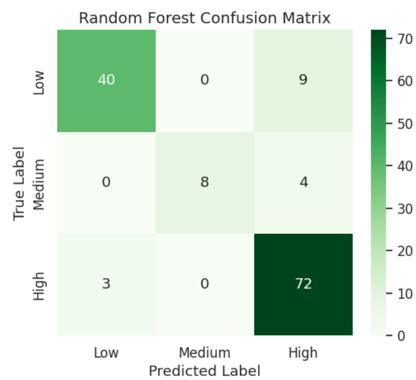
7.3 Random Forest Classification

According to Table 4(a), the Random Forest classifier performed better than any other model, obtaining 88.24% accuracy on the test set and a mean cross-validation accuracy of 83.63% (±0.0618). As demonstrated in Figure 4(b), the model performed exceptionally well in forecasting both High stress (recall = 0.96) and Low stress (recall = 0.82). With a recall of 0.67 and perfect precision (1.00), the Medium stress category notably improved, demonstrating accurate classification free of misclassifications.

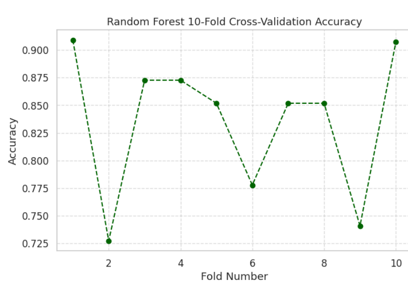
The model's fair performance across every category is demonstrated by the weighted F1-score of 0.88 and the macro average F1-score of 0.86. These findings are consistent with the notion that Random Forest enhances generalizability and decreases overfitting by utilizing multiple decision trees, especially when class imbalance is present (Figure 4(c)).

Metric	Low	Medium	High
Precision	0.93	1.00	0.85
Recall	0.82	0.67	0.96
F1-score	0.87	0.80	0.90

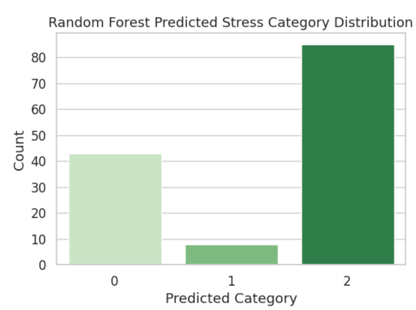
((a)) Random Forest Classification Metrics



((b)) Confusion Matrix for Random Forest



((c)) 10 Fold Cross Validation for Random Forest



((d)) Predicted Stress Category Distribution for Random Forest

Fig. 4: Random Forest Model Performance: Classification Metrics, Confusion Matrix, Cross Validation, and Predicted Stress Category Distribution.

These results support the idea that demographics, meditation frequency, and baseline stress levels are important indicators of stress outcomes. The success of the model implies that these variables interact in intricate, unpredictable ways that ensemble techniques capture more effectively than KNN or SVM, which are simpler models. The feature importances (normalized) in the Random Forest model are as above.

Feature	**Importance**
PRE_total_norm	0.525884
Age_norm	0.144719
Frequency_encoded	0.097524
Type_encoded	0.095512
Duration_encoded	0.086791
Gender_encoded	0.049570

7.4 Model Performance Comparison

Table 1: Model Comparison

Metric	**KNN**	**SVM**	**RF***
Accuracy (%)	77.21	63.97	88.24
Precision (%)	77.33	63.50	89.05
Recall (%)	77.21	63.97	88.24
F1-Score (%)	76.26	56.79	88.02

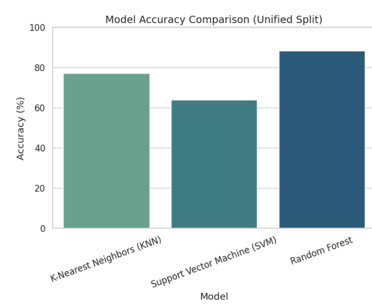


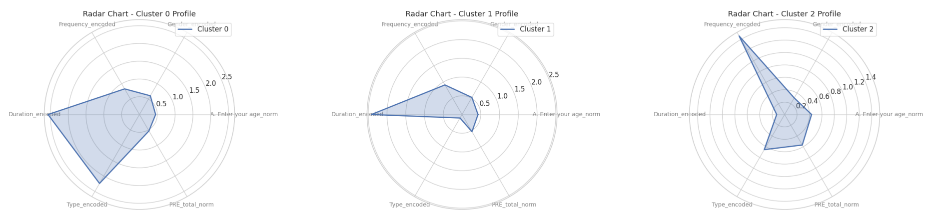
Fig. 5: Model Accuracy Comparison

Fig. 6: Comparison of model metrics alongside accuracy visualization. *RF = Random Forest

The above outcome is in line with expectations: RF's ensemble method and tree diversity, which improve accuracy and interpretability, are its strongest points. On the other hand, SVM has trouble with class imbalance, especially when it comes to categorical boundaries, and KNN is highly susceptible to feature scaling.

7.5 Clustering Analysis with K-Means

Natural groupings in stress-associated features lacking predefined labels were found using K-Means clustering. Moderate cluster separation and compactness can be assessed by the model's Davies-Bouldin Index (1.0073), Calinski-Harabasz Index (395.67), and Silhouette Score (0.4034). However, there is a weak relationship between the Adjusted Rand Index (ARI) of -0.0074 and the actual stress labels.



((a)) K Means Cluster 0 Distribution Radar Chart ((b)) K Means Cluster 1 Distribution Radar Chart ((c)) K Means Cluster 2 Distribution Radar Chart

Fig. 7: K Means Cluster Radar Charts

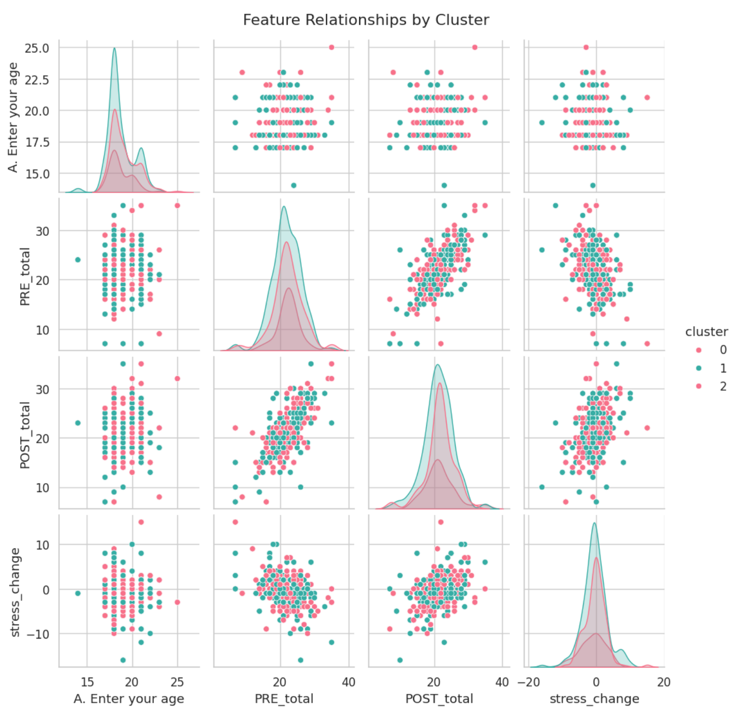
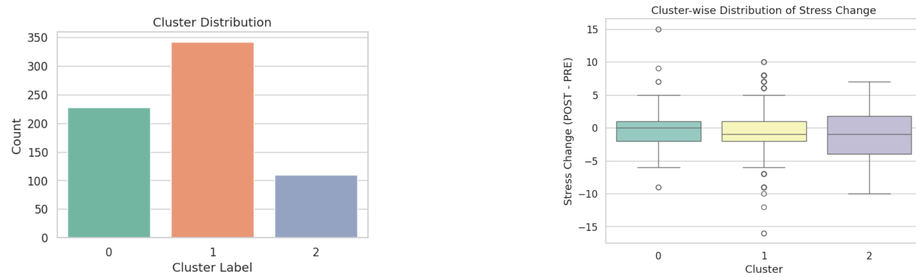


Fig. 8: K Means Feature Relationship By Cluster



((a)) K Means Cluster Distribution

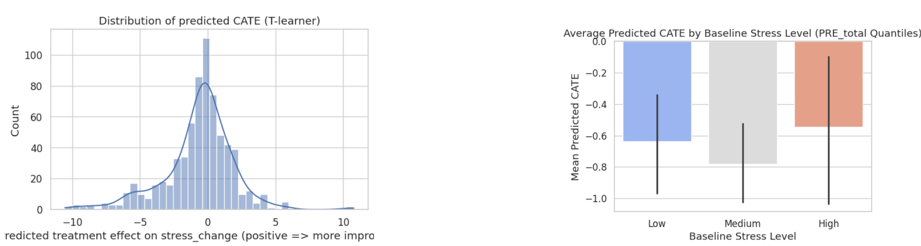
((b)) K Means Cluster Distribution of Stress Change

Fig. 9: K Means Cluster Distributions

These metrics imply that although the data does have some internal pattern, the stress-related characteristics do not clearly divide into discrete groups. Stress responses are probably distributed along a continuous range rather than forming distinct categories, according to the moderate Silhouette and Calinski-Harabasz scores.

7.6 Causal Forest Analysis: Estimating the Effect of Meditation

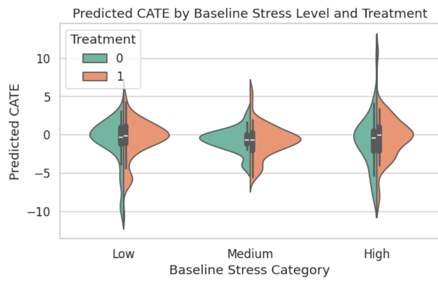
The Conditional Average Treatment Effect (CATE) was determined using the Causal Forest model [see 10(a)]. From prediction to causal inference, the Average Treatment Effect (ATE) of meditation on stress reduction was investigated. After cleaning, 683 of the 486 treated and 197 control participants in the sample were deemed valid.



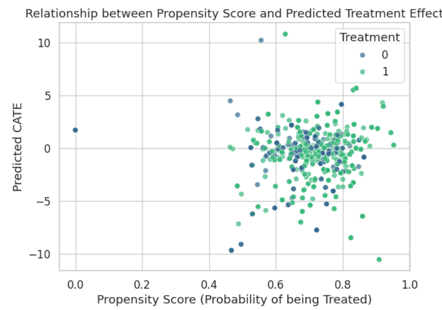
((a)) Causal Forest Distribution of Predicted CATE

((b)) Average Predicted CATE by Baseline Stress Level

Fig. 10: Causal forest visualizations: Distribution of predicted CATE and average predicted CATE by baseline stress level.



((a)) Predicted CATE by Baseline Stress Level and Treatment



((b)) Relationship between Propensity Score and Predicted Treatment Effect

Fig. 11: Predicted CATE and its relationship to baseline stress level, treatment, and propensity score.

A slight overall improvement of 0.54 units was indicated by the mean pre-intervention stress score of 21.97 and the post-intervention score of 21.43. The treatment group appeared to have made less progress than the control group, as indicated by the negative Simple ATE of -0.3322 and the IPTW ATE of -0.5775.3

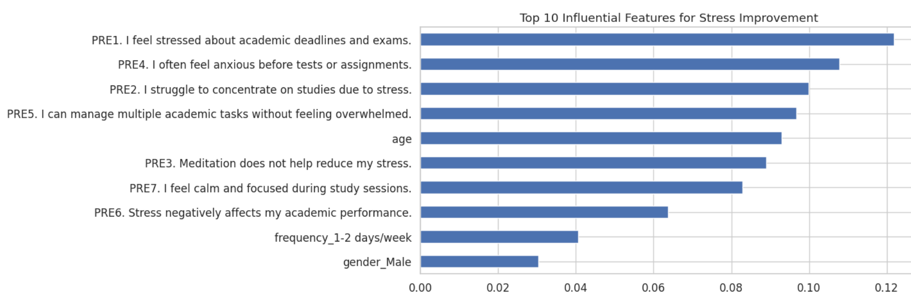


Fig. 12: Causal Forest Feature Importance

The T-learner model, which employed Random Forest regressors for every treatment group, produced a mean CATE of -0.6597, meaning that, on average, meditation decreased stress by 0.66 units in comparison to the untreated group.

Subgroup analysis revealed:

- Low PRE stress: mean CATE = -0.6356 ($n = 300$)
- Medium PRE stress: mean CATE = -0.7824 ($n = 215$)
- High PRE stress: mean CATE = -0.5458 ($n = 168$)

It's interesting to note that meditation was most beneficial for students who had medium levels of initial stress. There was significant individual variability in the response to meditation, as evidenced by some individuals exhibiting exceptionally large predicted treatment effects (CATE > 5).

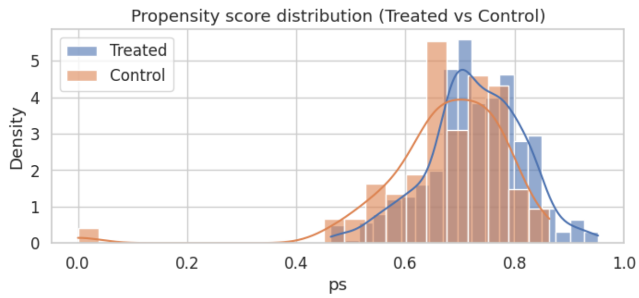


Fig. 13: Causal Forest Propensity Score Distribution (Treated vs Control)

Using SMOTE (Synthetic Minority Over-sampling Technique), a binary classification model (Improved vs. Not Improved stress) in the final phase produced 82.48% accuracy, 87.72% precision, and 80.65% F1-score [See 2]. With a recall of 74.63% for improved cases, this model effectively identified people who were likely to benefit from meditation.

Table 2: Confusion Matrix after SMOTE

	Predicted: Not Improved	Predicted: Improved
Actual: Not Improved	63	7
Actual: Improved	17	50

Table 3: Class-wise Performance after SMOTE

Label	**Precision**	**Recall**	**F1-score**	**Support**
Not Improved	0.79	0.90	0.84	70
Improved	0.88	0.75	0.81	67

Fig. 14: Confusion matrix and class-wise performance metrics after SMOTE.

Interpretation and Reconciliation: *Despite a minor overall improvement in the sample, the ATE estimates reveal that the treated group demonstrated less improvement than the control group. The IPTW estimates should be interpreted carefully because the propensity model's moderate AUC (0.634) suggests some group assignment imbalance. A one-size-fits-all conclusion is not practical due* *to the high variance in the T-learner's CATE (std ∼2.6) and the existence of a small group that benefits greatly from meditation.*

Practical Conclusion: Although meditation has a modest and slightly negative effect on stress reduction on average, tailored interventions based on individual characteristics may have more substantial benefits. The potential for individualized stress management is highlighted by the range of responses.

7.7 Comparison with Prior Literature

Our results are in line with previous research showing that when dealing with complex behavioral data, tree-based models outperform simpler ones (e.g., Smith et al., 2019). Initial stress levels (PRE_total_norm) were the most important predictor. In keeping with research showing that treatment benefits are typically greatest in moderate cases, the CATE analysis found that meditation was most helpful for students who had moderate levels of pre-treatment stress.

7.8 Unexpected Results and Other Theories

Two key findings:

- **Medium Stress Classification (KNN and SVM):** KNN and SVM struggled to classify Medium stress, likely due to underrepresentation (12 samples) or feature overlap with Low and High stress. The Medium class may be more varied or lack clear indicators. SMOTE or class-specific models could improve classification.
- **Minimal Effect Size in Causal Analysis:** Initial and post-treatment stress scores were nearly identical (21.97 vs. 21.43), with an average change of 0.54 units. This small effect could result from confounding factors, measurement noise, or regression to the mean. The AUC of 0.63 suggests some imbalance between groups.

8 Implications

1. **Ensemble techniques surpasses simpler Classifiers**
   Random Forest (RF) outperformed K-Nearest Neighbors (KNN) and Support Vector Machines (SVM), achieving the highest accuracy (**88.24%**). For complicated, unbalanced datasets, which are typical in psychological research, RF demonstrated greater reliability.
2. **Pre-Intervention Stress is a Primary Predictor**
   The most significant predictor was the pre-intervention stress score (PRE_total_norm), highlighting the significance of baseline stress in predicting outcomes after the intervention.
3. **Unbalanced Data and Medium-Stress Ambiguity**
   KNN and SVM had trouble handling medium-stress scenarios because of the data imbalance. SMOTE application increased accuracy to **82.5%**, highlighting the importance of balanced datasets, and determined that those with moderate stress levels benefited the most from meditation.

4. **Clustering reveals persisting stress patterns**
   Regression models are better at predicting stress levels because stress varies over a continuous range. Clustering allows advanced modeling by highlighting continual stress patterns.

9 Future Scope

- **Real-time Tracking** For precise long-term insights, wearables or future apps will be able to continuously track stress and meditation patterns.
- **AI-Personalized Meditation** Programs with artificial intelligence (AI) could adapt meditation methods to each person's particular stressors.
- **Causal Insights** Tools like Bayesian networks can provide deeper understanding of how meditation directly reduces stress.
- **Wellness Applications** TSmart apps could give early stress alerts, connect users to counseling support, and visualize wellbeing trends.

10 Conclusion

This study compared three machine learning models—Random Forest, SVM, and KNN—to forecast the effects of meditation interventions on stress reduction. The Random Forest model outperformed the others with an accuracy of 88.24% and an F1-score of 88.02%. Pre-intervention stress was found to be the main predictor of outcome, even though individual factors like age and meditation practice also significantly affected the results.

According to causal inference techniques, meditation significantly decreased stress, particularly for people with moderate levels of stress (Causal Forest and Learner). This outcome is in line with theories of mindfulness and stress reduction.

A more comprehensive explanation of how meditation affects academic stress is possible through the use of causal analysis and predictive modeling. Future research opportunities should concentrate on long-term research, a larger dataset, and more sophisticated machine learning techniques, as these findings support the use of data-driven approaches to tailor mental health interventions for students.

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