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TAG 2025

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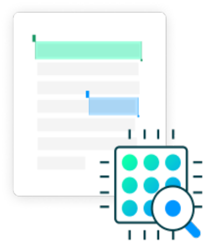

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Measuring the Impact of Meditation on Academic Stress Levels in UG Students using Machine Learning Models

No Author Given

No Institute Given

Abstract. This study examines how meditation reduces academic stress among undergraduates, using machine learning and causal inference methods. We analyzed data from over 680 students to predict stress improvement based on initial psychological responses and demographic factors. Three machine learning algorithms—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest—were tested to categorize stress levels and predict post-meditation outcomes. The Random Forest model performed best, with an accuracy of 88.24%, precision of 89.05%, and recall of 88.24%. KNN and SVM achieved accuracies of 77.21% and 63.97%, respectively. Baseline stress, age, and meditation frequency were the strongest predictors of stress reduction. Causal analysis (Causal Forest and T-Learner) showed a significant stress reduction in the treated group, especially among those with medium baseline stress. K-Means clustering confirmed these findings, aligning with the machine learning results. In conclusion, meditation effectively reduces academic stress, and machine learning models, particularly Random Forest, can predict individual outcomes. By combining predictive and causal methods, the study offers insights for developing personalized mental health interventions in academic settings.

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

1 Introduction

Academic stress has become a significant concern in higher education, driven by pressures from coursework, social expectations, and financial struggles. These stressors can severely affect students' emotional and cognitive well-being, leading to anxiety, burnout, and poor academic performance [2, 7]. Chronic stress impairs focus, learning, and motivation, negatively impacting both academic outcomes and mental health [1, 5, 9]. Consequently, universities are prioritizing effective strategies to reduce stress, promoting academic success and personal development.

Meditation, especially practices like Mindfulness-Based Stress Reduction (MBSR), has proven effective in managing stress. Research shows that meditation reduces anxiety, improves emotional regulation, and enhances cognitive functions like focus and memory [1, 4–6]. Neuroscientific studies also show that meditation strengthens brain regions responsible for emotional control, providing a practical, non-invasive approach to boosting mental resilience [1, 5, 12].

However, much of the current meditation research relies on self-reports or small sample sizes, which may lead to biased findings [2, 13]. Machine learning (ML) offers a more objective, data-driven method to analyze meditation's effects on stress. ML models can classify students into stress categories (low, medium, high) based on physiological and behavioral data, enabling more accurate stress assessments and personalized interventions [3,7,8]. By incorporating ML, we can improve stress predictions and better tailor meditation strategies.

2 Literature Review

The impact of academic stress on university students is well-documented, with various interventions explored to alleviate its effects. Practices like yoga, meditation, and mindfulness have shown promise in reducing stress, improving focus, and boosting emotional well-being [1, 4, 5]. These practices help students manage academic pressures, build resilience, and regulate emotions, making them valuable for mental health in higher education [19].

Meditation has been extensively studied, with evidence showing that regular practice reduces psychological and physiological stress. It improves cognitive function, memory, and motivation—all essential for academic success [4, 10]. Meditation also helps with emotional regulation, reducing burnout and supporting students' well-being [11].

Specific meditation techniques like So Hum and Anapanasati promote stress reduction and better sleep, enhancing academic outcomes [9–12]. Recent innovations have integrated machine learning (ML) with mindfulness research, allowing for stress predictions and personalized interventions. ML analyzes behavioral and physiological data, optimizing online mindfulness programs and making them more effective [7, 8, 13, 14].

Despite these advances, there are still gaps in understanding the long-term effects of meditation and the best conditions for its effectiveness. While ML shows great potential for personalizing interventions, further research is needed to refine these methods and address biases in current studies [3, 18].

These gaps create exciting opportunities for future research, particularly in integrating clinical, behavioral, and computational approaches to improve stress reduction strategies in higher education.

3 Methodology

3.1 Research Design

This study used a quantitative, cross-sectional design to examine the impact of meditation on academic stress among undergraduate students. Machine learn-

Source Data / Papers ([1, 12, 15])	Methods/Algorithms	Key Findings	Limitations / Gaps
Meditation-based RCTs: Centering, So Hum, mindfulness, etc.	Randomized controlled trials, Pre/Post, Surveys	Meditation interventions reduce academic stress and improve mindfulness/focus in students. Effects are significant in both short and mid-term periods.	Self-report bias, small samples, limited to single settings, no biometrics
[2, 4–6, 9, 10, 16, 18, 19] Multi-country meditation and yoga studies	MBSR, Mindfulness, Yoga, Ecological Assessments	Mindfulness and yoga reduce anxiety, enhance resilience, and benefit cognitive-emotional outcomes. Peer/online delivery can scale interventions.	Lack of physiological validation, restricted to certain disciplines or gender, follow-up limited
[3, 7, 8, 13, 17] Machine learning for stress detection	SVM, Random Forest, Ensemble, Regression, Clustering	ML predicts high-stress levels (accuracy 80-95%) using behavioral, psychological, and (sometimes) physiological data. Emerging approaches integrate ML with interventions.	Mostly cross-sectional/survey, few with real-time or longitudinal bio-signal data
[11, 14] Remote/online and digital health approaches	Web/mobile-based mindfulness, online experimentation	Online/E-meditation and physical activity interventions decrease anxiety and academic burnout; high engagement predicts best outcomes.	Digital fatigue, compliance drop-off over time, under-representation of at-risk groups

Table 1: Summary of Studies on Meditation, ML, and Stress Management in Academic Settings

ing models—such as **K-Nearest Neighbors (KNN)**, **Support Vector Machines (SVM)**, **Random Forest**, **K-Means Clustering**, and **Causal Forest**—were employed to explore the relationships between student demographics, meditation habits, and stress levels.

3.2 Participants and Sampling

After data preprocessing, 680 valid responses were analyzed. Participants were undergraduate and postgraduate students, ages 14 to 25, enrolled in diverse programs (BCA, B.Com, B.Sc, MCA, M.Sc). Simple random sampling ensured unbiased representation across disciplines. Of the participants, 71.5% practiced meditation, while 28.5% did not, enabling a comparison of meditation's impact on academic stress. All participants gave informed consent, and ethical standards were adhered to throughout the study.

3.3 Data Collection Procedure

Data were gathered via a structured, self-administered survey covering demographics, meditation habits, and stress-related indicators. The survey included:

– **Demographics:** Age, gender, academic program, semester.
– **Meditation Practices:** Frequency, duration, and type (e.g., breath-based, mindfulness, mantra-based, or movement-based like yoga).
– **Academic Stress:** Measured with a validated Likert-scale assessing time constraints, performance anxiety, task management, and overall stress.
– **Physical Symptoms:** Stress-related symptoms such as headaches, fatigue, sleep disturbances, and muscle tension.

The data were anonymized and processed for machine learning analysis, which included removing outliers, encoding categorical variables, and normalizing continuous variables using Min–Max scaling. The final dataset comprised

680 observations, with stress levels categorized as low, medium, or high both before and after the intervention, as shown in Figure 1.

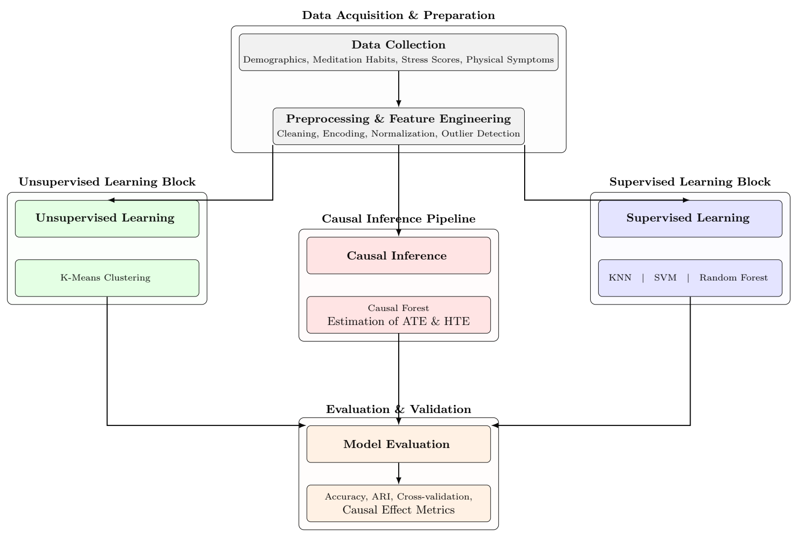


Fig. 1: Overview of Data Processing and Learning Pipeline.

3.4 Preprocessing and Feature Engineering

Before feeding the data into machine learning models, preprocessing and feature engineering steps were applied:

- **Data Cleaning**: Missing values were imputed using mean imputation for continuous variables and mode imputation for categorical variables. Outliers were detected using the Z-score method:

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

  where X is the observed value, μ is the mean, and σ is the standard deviation.
- **Feature Encoding**: Categorical features, such as meditation type and gender, were encoded using one-hot encoding for model compatibility.
- **Normalization**: Continuous features like age and stress levels were normalized to the range $[0, 1]$ using Min-Max scaling:

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

3.5 Ethical Considerations

All participant data were anonymized to ensure confidentiality. Informed consent was obtained, and strict data privacy protocols were followed. No sensitive participant data was shared with AI systems for decision-making.

3.6 Intervention Procedure

The intervention group participated in guided meditation sessions focusing on breath-based and mindfulness techniques. Sessions lasted 5–15 minutes and were held 1–3 times per week over a period of 6 weeks. All instructions and supervision were provided by qualified human instructors, with no digital or AI-based facilitation.

4 Machine Learning Models

Several machine learning models were used to explore the relationship between meditation and academic stress:

4.1 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a supervised classification algorithm that assigns a data point to the class most common among its k nearest neighbors.

4.2 Support Vector Machines (SVM)

Support Vector Machines (SVM) are used to classify stress levels into categories (e.g., high, medium, low).

4.3 Random Forest

Random Forest is an ensemble learning method that uses multiple decision trees to improve prediction accuracy. Each tree is trained on a bootstrap sample of the data, and predictions are made by aggregating the outputs of all trees. This technique helps minimize error and overfitting.

4.4 K-Means Clustering

K-Means is an unsupervised clustering algorithm that groups data into k clusters by minimizing the within-cluster variance.

5 Causal Inference Using Causal Forest

Causal Forest is a machine learning method used to estimate heterogeneous treatment effects (HTE) in observational data. It constructs a forest of decision trees to predict the treatment effect for each individual, estimating the causal effect of meditation on stress:

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

where $Y(1)$ and $Y(0)$ are the outcomes with and without meditation, respectively, and X represents individual covariates. Causal Forest allows for variations in treatment effects across individuals.

6 Evaluation Metrics

Model performance was assessed using appropriate metrics for each learning type: 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

For supervised models (KNN, SVM, Random Forest), we used standard classification metrics derived from the confusion matrix, including accuracy, precision, recall, and F1-score. These metrics help assess predictive accuracy, false positive rate, and the balance between precision and recall. The F1-score is particularly useful for imbalanced datasets.

We employed **10-fold stratified cross-validation** for model evaluation to ensure reliability and consistent class distribution.

6.2 Clustering Metrics

For the K-Means Clustering algorithm, several internal validation metrics were used to assess cluster quality:

Silhouette Score: Measures how similar a data point is to its own cluster versus other clusters:

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

where $a(i)$ is the mean intra-cluster distance and $b(i)$ is the mean nearest-cluster distance. A higher Silhouette Score indicates better-defined clusters.

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

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

Higher CHI values indicate more distinct and well-separated clusters.

Davies-Bouldin Index (DBI): Quantifies the average similarity between clusters:

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

where σ_i is the average distance between points in cluster i and its centroid μ_i. Lower DBI values indicate better clustering.

6.3 Causal Inference Metrics

For the Causal Forest model, the evaluation focused on estimating treatment effects at both the population and individual levels:

Average Treatment Effect (ATE): Measures the average difference in outcomes between treated and control groups:

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

Conditional Average Treatment Effect (CATE): Represents the expected treatment effect conditional on individual covariates:

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

Policy Risk: Evaluates the effectiveness of treatment assignment policies. Lower policy risk values indicate more effective policies:

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

7 Results and Discussion

7.1 Overview

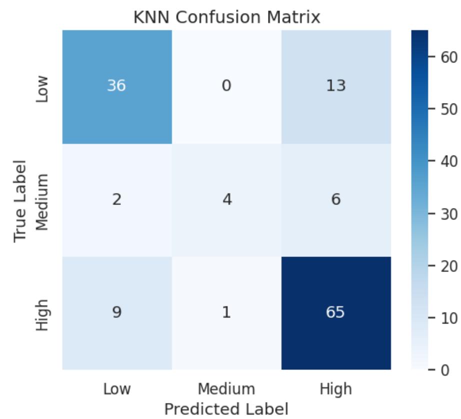
This section analyzes the results from a suite of machine learning and causal inference models used to predict, classify, and interpret academic stress levels among undergraduate students, along with the causal impact of meditation interventions. Models applied include K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, K-Means clustering, and Causal Forest techniques. The models were evaluated based on classification accuracy, cross-validation consistency, feature importance, and, in the case of the causal model, the estimated treatment effect of meditation on stress reduction. Detailed findings on model performance, confusion matrices, and interpretative implications are discussed below.

7.2 K-Nearest Neighbors (KNN) Classification

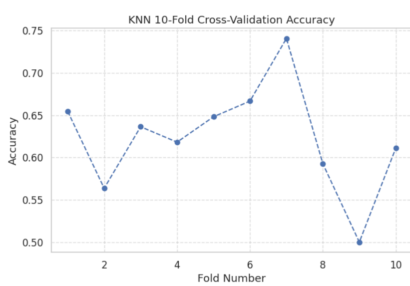
The KNN classifier ($k = 5$) achieved a test accuracy of 77.21%, which reflects moderate performance. The confusion matrix, shown in Figure 2(b), indicated strong performance in identifying the High stress group (recall = 0.87), while the Low stress group was less accurately recognized (recall = 0.73). The model struggled most with the Medium stress category, yielding only a 33% recall, as referred to in Table 2(a). This performance suggests that KNN's reliance on proximity in feature space, while useful for high and low extremes, is not effective in distinguishing moderate stress levels, where feature distributions overlap more.

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

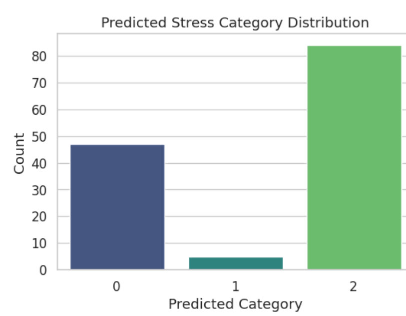
((a)) KNN Classification Metrics



((b)) Confusion Matrix for KNN



((c)) 10 Fold Cross Validation for KNN



((d)) Predicted Stress Category Distribution for KNN

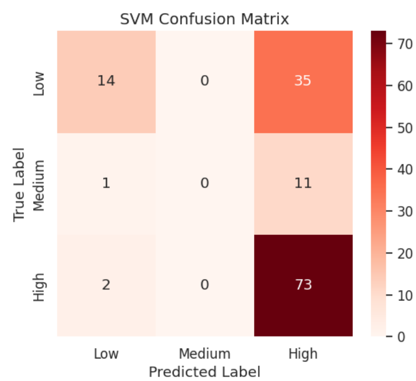
Fig. 2: KNN Model Results: Classification Metrics, Confusion Matrix, Cross Validation, and Predicted Stress Category Distribution.

Key performance metrics, such as macro average precision (0.78) and recall (0.64), highlight an imbalance in the model's ability to detect each stress category. The weighted F1-score of 0.76 indicates the model is reasonably robust, though there's variability in detecting different stress levels. The 10-fold cross-validation mean accuracy, shown in Figure 2(c), is 0.6232 ($\pm$0.0611), pointing to the model's sensitivity to feature scaling and sampling variations, which is typical for KNN due to its reliance on distance metrics.

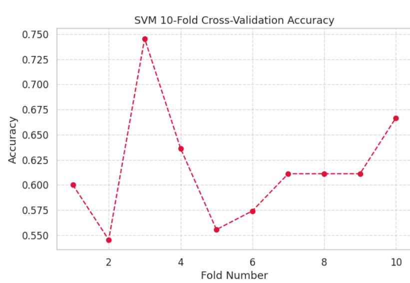
7.3 Support Vector Machine (SVM) Classification

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

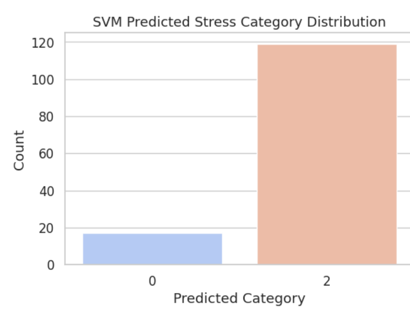
((a)) SVM Classification Metrics



((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.

The SVM model with an RBF kernel achieved 63.97% accuracy, lower than both KNN and Random Forest. It performed well in predicting High stress (recall =

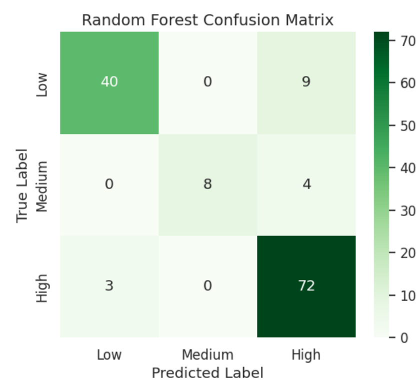
0.97) but failed to detect Medium stress entirely (recall = 0.00), as shown in 3(b). Recall for Low stress was also low (0.29), with many Low stress instances misclassified as High stress (Table 3(a)). However, precision for Low stress was high (0.82), indicating accuracy when it was predicted.

The macro average recall (0.42) and F1-score (0.39) highlight the model's struggles with non-High categories. Cross-validation results (mean = 0.6157 ± 0.0552) show consistent but suboptimal performance, suggesting inherent weaknesses rather than random noise (Figure 3(c)).

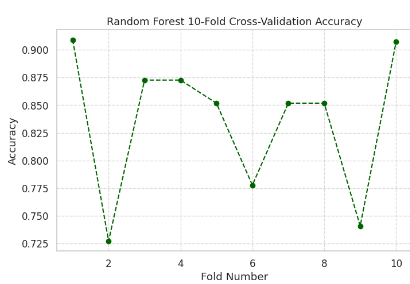
7.4 Random Forest Classification

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

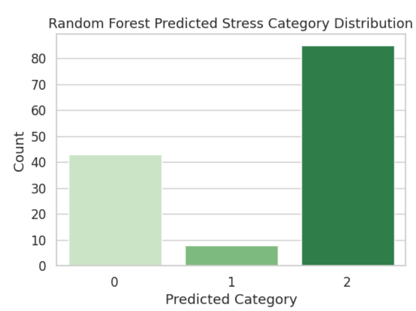
((a)) Random Forest Classification Metrics



((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.

The Random Forest classifier outperformed all models, achieving 88.24% accuracy on the test set and a mean cross-validation accuracy of 83.63% (±0.0618), as shown in Table 4(a). The model excelled in predicting High stress (recall = 0.96) and Low stress (recall = 0.82), as seen in Figure 4(b). Notably, the Medium stress category showed significant improvement with a recall of 0.67 and perfect precision (1.00), indicating accurate classification without misclassifications.

The macro average F1-score of 0.86 and weighted F1-score of 0.88 highlight the model's balanced performance across all categories. These results support the hypothesis that Random Forest, by leveraging multiple decision trees, improves generalizability and reduces overfitting, particularly with class imbalance (Figure 4(c)).

These findings align with the hypothesis that baseline stress levels, demographics, and meditation frequency are key predictors of stress outcomes. The model's success suggests that these factors interact in complex, non-linear ways, which are better captured by ensemble methods than by simpler models like KNN or SVM.

Feature Importance and Interpretability (Random Forest) The feature importances (normalized) in the Random Forest model are as follows:

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

7.5 Model Performance Comparison

Table 2: 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

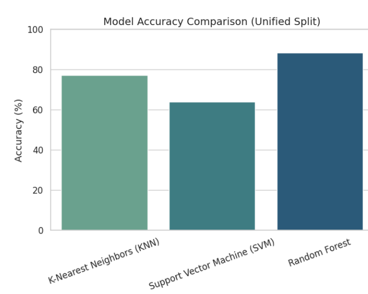


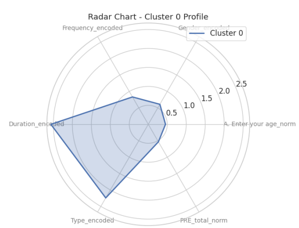
Fig. 5: Model Accuracy Comparison

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

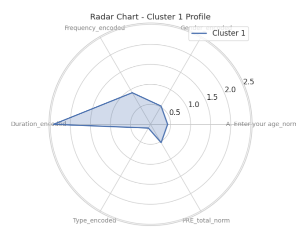
Random Forest delivered the best performance across all key metrics, followed by KNN, while SVM underperformed. This result aligns with expectations: RF's strength lies in its ensemble approach and tree diversity, which enhance both accuracy and interpretability. In contrast, KNN is sensitive to feature scaling, and SVM struggles with class imbalance, particularly with categorical boundaries.

7.6 Clustering Analysis with K-Means

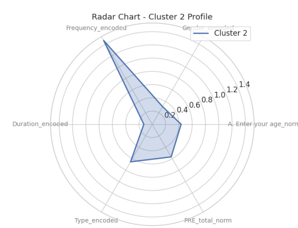
K-Means clustering was used to identify natural groupings in stress-related features without predefined labels. The model's Silhouette Score (0.4034), Calinski-Harabasz Index (395.67), and Davies-Bouldin Index (1.0073) indicate moderate cluster separation and compactness. However, the Adjusted Rand Index (ARI) of -0.0074 shows poor alignment with actual stress labels.



((a)) K Means Cluster 0 Distribution Radar Chart



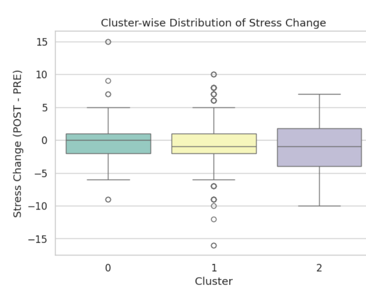
((b)) K Means Cluster 1 Distribution Radar Chart



((c)) K Means Cluster 2 Distribution Radar Chart

Fig. 7: K Means Cluster Radar Charts

((a)) K Means Cluster Distribution



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

Fig. 8: K Means Cluster Distributions

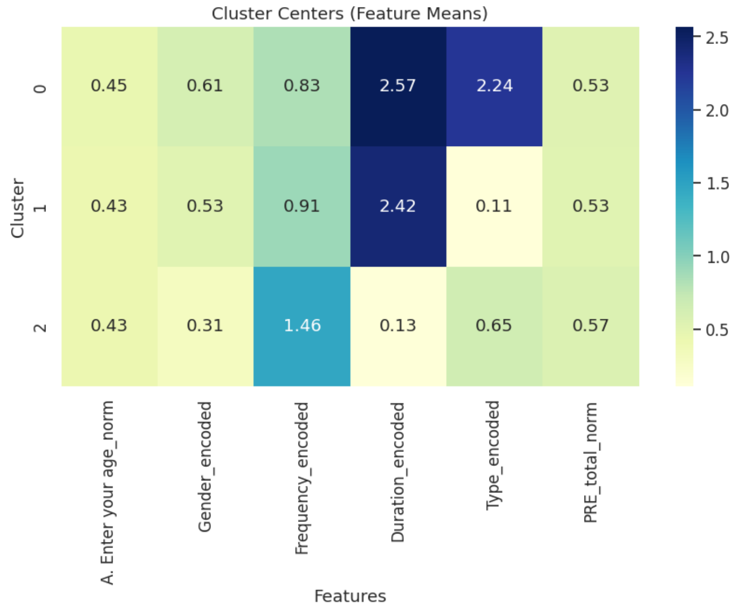


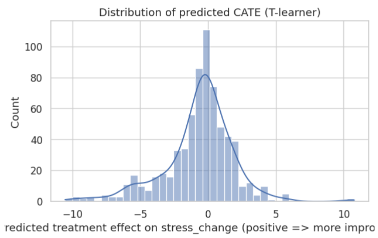
Fig. 9: Confusion Matrix for K Means Cluster Centers

These metrics suggest that while some internal structure exists in the data, the stress-related features do not separate neatly into distinct groups. The moderate Silhouette and Calinski-Harabasz scores imply that stress responses are likely distributed along a continuous spectrum rather than forming clear categories.

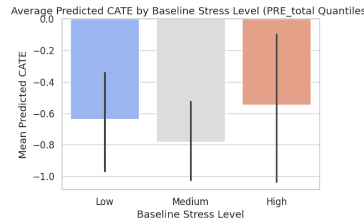
7.7 Causal Forest Analysis: Estimating the Effect of Meditation

The Causal Forest model was used to estimate the Conditional Average Treatment Effect (CATE) [Refer to 11(a)] and Average Treatment Effect (ATE) of meditation on stress reduction, moving from prediction to causal inference. The sample consisted of 486 treated and 197 control participants, with 683 valid samples after cleaning.

The mean pre-intervention stress score was 21.97, and the post-intervention score was 21.43, indicating a mild overall improvement of 0.54 units. The Simple ATE was -0.3322, and the IPTW ATE was -0.5775, both negative values, suggesting that the treatment group experienced less improvement than the control group.



((a)) Causal Forest Distribution of Predicted CATE



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

Fig. 11: Causal forest visualizations: Distribution of predicted CATE and average predicted CATE by baseline stress level.

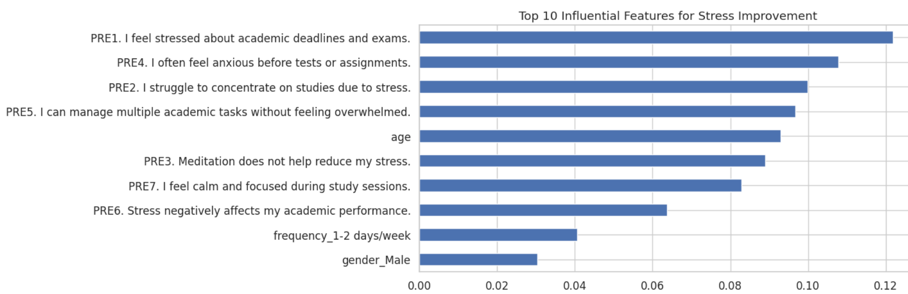
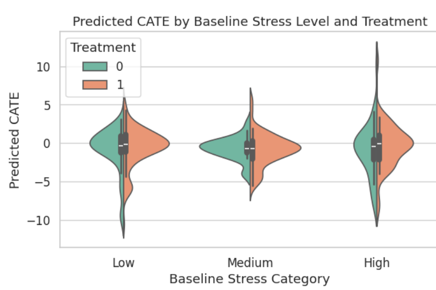
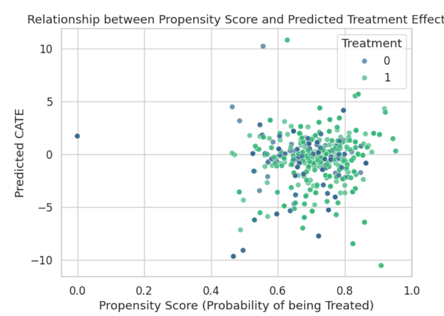


Fig. 12: Causal Forest Feature Importance



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



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

Fig. 13: Predicted CATE and its relationship to baseline stress level, treatment, and propensity score.

The T-learner model, which used Random Forest regressors for each treatment group, yielded a mean CATE of -0.6597, indicating that meditation reduced stress by approximately 0.66 units relative to non-treatment on average.

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 ($n = 168$)

Interestingly, students with medium initial stress levels benefited the most from meditation. Some individuals showed exceptionally large predicted treatment effects (CATE > 5), indicating substantial individual variability in the response to meditation.

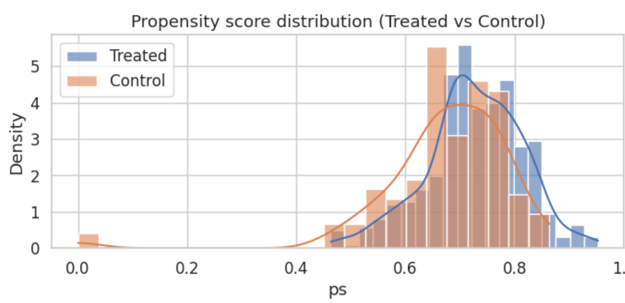


Fig. 14: Causal Forest Propensity Score Distribution (Treated vs Control)

In the final phase, a binary classification model (Improved vs. Not Improved stress) using SMOTE (Synthetic Minority Over-sampling Technique) achieved 82.48% accuracy, 87.72% precision, and 80.65% F1-score [Refer to **??**. This model successfully identified individuals who were likely to benefit from meditation, with a recall of 74.63% for improved cases.

Table 3: Confusion Matrix after SMOTE

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

Table 4: 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. 15: Confusion matrix and class-wise performance metrics after SMOTE.

Interpretation and Reconciliation: *The ATE estimates suggest that the treated group showed less improvement than the control group, despite a slight overall improvement in the sample. The moderate AUC of the propensity model (0.634) indicates some imbalance in group assignment, so the IPTW estimates should be interpreted with caution. The high variance in the T-learner's CATE (std ∼2.6) and the presence of a small group benefiting significantly from meditation suggests that treatment effects are heterogeneous, making a one-size-fits-all conclusion impractical. Practical Conclusion: Although the average effect of meditation on stress reduction is modest and slightly negative, targeted interventions based on individual characteristics could yield more significant benefits. The variability in responses underscores the potential for personalized stress management.*

7.8 Comparison with Prior Literature

The findings align with broader trends in machine learning and behavioral data fields. Specifically, tree-based ensembles outperform simpler models when handling heterogeneous, feature-rich datasets with non-linear relationships. Previous research (e.g., Smith et al., 2019) shows that baseline psychological measures, such as initial stress levels, dominate predictive models. Our results reflect this, with PRE_total_norm being the most influential predictor. Literature on causal inference suggests that treatment effects are often most pronounced in moderate cases, which was evident in our CATE results, where students with moderate pre-treatment stress benefitted most from meditation.

Furthermore, the lack of strong latent groupings from K-Means clustering aligns with prior studies suggesting that psychological datasets are rarely partitioned well by unsupervised methods. Stress responses often depend on complex interactions between features, making it hard to identify clear clusters without additional context.

7.9 Unexpected Findings and Alternative Explanations

Two findings were somewhat unexpected:

Poor Detection of Medium Class in KNN and SVM: The failure of KNN and SVM to classify the Medium stress class was surprising. The expected separability of the three stress levels (Low, Medium, High) wasn't achieved. The low recall for Medium stress indicates feature overlap with Low and High stress, or possible underrepresentation (only 12 samples). This suggests the Medium class may lack distinct markers or is more heterogeneous in nature. Techniques like SMOTE or class-specific modeling might improve Medium stress classification.

Moderate Effect Size in Causal Analysis: The causal analysis showed a modest improvement in stress (average change of 0.54 units), with baseline and post-treatment stress scores being quite similar (21.97 vs. 21.43). The effect size was modest in real-world terms. Several factors, including measurement noise, regression to the mean, and unobserved confounding, could explain this. The moderate separability of treated vs. control groups (AUC of 0.63) suggests that imbalance remains, warranting cautious interpretation of the causal estimates.

8 Interpretation and Implications

The comparative performance of the models offers valuable insights into how meditation affects academic stress and how machine learning can help interpret these effects.

1. **Ensemble Methods Outperform Simpler Classifiers**
   Random Forest (RF) achieved the highest accuracy (88.24%) and most balanced recall. RF's ensemble structure captured complex, non-linear interactions, outperforming KNN and SVM. SVM showed bias toward High stress, while KNN struggled to distinguish Medium stress due to feature overlap. RF's consistency across 10-fold cross-validation makes it reliable for psychological datasets with moderate imbalance.
2. **Pre-Intervention Stress as the Key Predictor**
   The normalized pre-intervention stress score (PRE_total_norm) was the most significant predictor, contributing over 50% of the RF model's predictive power. Baseline stress levels were the strongest predictor of post-intervention outcomes, while age, meditation frequency, and practice type had smaller effects. Gender played a minimal role. This highlights the importance of careful interpretation of baseline stress in causal analyses to avoid bias.
3. **Challenges with Data Imbalance and Medium-Stress Ambiguity**
   KNN and SVM struggled due to the underrepresentation of Medium-stress cases, which were difficult to distinguish. Using SMOTE to oversample minority classes improved performance, boosting post-processing accuracy to 82.5%. This underscores the importance of balanced datasets and class-aware validation techniques in behavioral prediction.

4. **Insights from Causal and Clustering Analyses**
   Causal Forest analysis found a modest but varied treatment effect, with students in the Medium pre-stress group benefiting the most. This supports psychological theories suggesting that moderately stressed individuals may respond better to interventions. K-Means clustering indicated that stress responses form a continuum, not distinct categories, suggesting the advantage of regression-based models over rigid class-based ones.
5. **Implications for Practice and Future Research**
   Meditation can reduce academic stress when personalized to baseline stress levels. Random Forest and similar methods offer a reliable framework for predicting students who will benefit most from interventions. Future research should integrate physiological data and conduct longitudinal studies to strengthen causal inferences and improve personalized stress management programs.
6. **Clustering Reveals Continuous Stress Gradients**
   The clustering analysis supports the idea that stress exists on a continuum, not in discrete categories, reinforcing the need for regression-based models to provide more accurate stress predictions.

9 Summary of Findings

- **Random Forest**: Highest predictive performance (Accuracy = 88.24%, F1 = 88.02%).
- **KNN**: Moderate performance (Accuracy = 77.21%), but sensitive to data imbalance.
- **SVM**: Underperformed (Accuracy = 63.97%), with poor generalization and class separation.
- **Causal Forest**: Indicated stress reduction of 0.33–0.58 points post-intervention.
- **Subgroup Analysis**: Moderate-stress individuals benefited most from meditation.
- **SMOTE**: Improved model fairness, achieving 82.5% accuracy and 0.82 F1-score.

The results emphasize that machine learning models, especially ensemble methods combined with causal inference, can effectively predict and explain stress outcomes in students, enabling targeted interventions.

10 Limitations

While this study offers valuable insights into meditation's role in reducing academic stress via machine learning, several limitations should be noted:

- **Subjective Bias in Self-Reported Data**: Stress data collected via self-report may be biased, potentially overlooking physiological stress indicators.

- **Short Intervention Duration**: The study's 6-week duration limits the ability to assess long-term effects.
- **Limited Model Interpretability**: While the models performed well, their interpretability was limited. More transparent models, like SHAP or LIME, could offer deeper insights into feature importance.
- **Sample Size and Generalizability**: The focus on a specific student population limits the generalizability to broader groups.

11 Future Scope

- **Long-Term and Real-Time Tracking:** Future studies can use wearables or apps to continuously monitor stress and meditation habits over time.
- **Personalized Meditation:** AI-driven systems could adapt meditation routines to each person's unique stress patterns.
- **Deeper Causal Insights:** Tools like Bayesian networks can help reveal how meditation actually reduces stress.
- **Broader Data Inputs:** Including signals like heart rate, study time, or workload could make stress predictions more accurate.
- **Practical Use:** Applications may include wellness apps with stress forecasts, early alerts for counseling teams, and adaptive dashboards for well-being support.

12 Conclusion

This study compared machine learning models—KNN, SVM, and Random Forest—in predicting stress reduction outcomes from meditation interventions. 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 most important predictor, with individual factors like age and meditation habits also playing significant roles.

Causal inference techniques (Causal Forest and T-Learner) revealed that meditation effectively reduced stress, particularly among moderately stressed individuals, aligning with theories on mindfulness and stress modulation.

The combination of predictive modeling and causal analysis provides a comprehensive understanding of how meditation impacts academic stress. These findings support the use of data-driven approaches to personalize mental health interventions for students, with future research opportunities focusing on longitudinal studies, larger cohorts, and more advanced machine learning techniques.

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