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

Akshay S[1], Pujith Yerapathi[2], Darshan Suresh[3], Ponnanna K K[4], Adithya Vinod[5]

Department of Computer Science, Amrita School of Computing,
Amrita Vishwa Vidyapeetham, Mysuru Campus, Karnataka, India

[1]s_akshay@my.amrita.edu, [2]ypujith@gmail.com, [3]darshansuresh1804@gmail.com,
[4]ponnannakk9019@gmail.com, [5]aadivinod66@gmail.com

***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.

***Index Terms*—Machine Learning, Meditation, Academic Stress, Mindfulness, Stress Management,**

I. Introduction

Academic stress has become a major concern in higher education, as students face pressures from coursework, social life, and finances, leading to anxiety and burnout [2], [7]. Chronic stress impairs emotional balance and cognitive function, affecting focus, learning, and overall well-being [1], [5], [9]. Universities are prioritizing strategies to reduce stress and improve both academic performance and personal development.

Stress arises when academic demands exceed a student's coping abilities [17]. Common stressors include exams, deadlines, peer competition, and financial issues [2]. The COVID-19 pandemic further exacerbated these challenges, increasing isolation and digital fatigue [2]. These stressors often result in reduced motivation, poor memory retention, and compromised decision-making.

Meditation has proven effective in managing stress, with practices like Mindfulness-Based Stress Reduction (MBSR) shown to reduce anxiety, improve focus, and regulate emotions [1], [4]–[6]. Neuroscientific studies indicate that meditation enhances brain areas involved in emotional regulation, making it a non-invasive, accessible tool for improving mental clarity and resilience [1], [5], [12].

While existing research highlights the benefits of meditation, much of it relies on self-reports or small samples, leading to potential biases [2], [13]. To address this, machine learning (ML) offers a powerful, data-driven approach for analyzing stress and meditation outcomes more precisely [3], [7], [8]. ML models can analyze a variety of data—ranging from physiological signals to behavioral patterns—helping quantify stress and assess the impact of meditation on students' well-being.

In this context, ML enables stress classification and treatment effect estimation. For instance, models can predict stress levels based on student features:

$$S_i = \alpha_1 X_{i1} + \alpha_2 X_{i2} + \cdots + \alpha_n X_{in} + \epsilon_i \tag{1}$$

where S_i is the stress level, X_{ij} are the features, and ϵ_i is the error term. For classification, ML can assign students to stress categories (low, medium, high):

$$\hat{y}_i = f_\theta(X_i), \quad \hat{y}_i \in \{\text{Low, Medium, High}\} \tag{2}$$

This approach allows for personalized interventions and biofeedback, combining meditation with ML to provide scalable, data-driven solutions for managing academic stress and improving mental health [2], [13].

II. Literature Review

Academic stress is a leading mental health concern among university students. In response, interventions like yoga, meditation, and mindfulness have been explored to improve emotional and psychological well-being. These practices have been shown to reduce stress, enhance focus, and improve self-awareness [1], [4], [5].

Yoga, for example, improves emotional balance, resilience, and focus, helping students manage academic pressures [19]. Meditation practices like So Hum and Anapanasati also reduce stress and improve sleep, contributing to better academic performance [9], [12].

Meditation's benefits are well-documented, with regular practice reducing both psychological and physiological stress. It improves cognitive function, memory, and motivation [4], [10], making it a powerful tool for students under academic pressure. Meditation has also been linked to improvements in emotional regulation and resilience, acting as a preventive measure against burnout [11].

Recent research has explored integrating technology with mindfulness practices, using machine learning (ML) to predict stress patterns and personalize mindfulness interventions. ML tools analyze behavioral and physiological data to offer targeted strategies for managing stress [7], [8], [13], [14]. These technological approaches have been effective in optimizing online mindfulness programs, helping students manage stress more efficiently.

In conclusion, yoga, meditation, and mindfulness have proven effective in reducing academic stress, enhancing emotional regulation, and improving cognitive function. The integration of ML with these practices holds great promise for personalized, data-driven approaches to supporting student mental health and academic success [3], [18].

III. Methodology

A. Research Design

This study used a quantitative, cross-sectional design to assess the impact of meditation on academic stress among undergraduate students. Machine learning models, including **K-Nearest Neighbors (KNN)**, **Support Vector Machines (SVM)**, **Random Forest**, **K-Means Clustering**, and **Causal Forest**, were applied to analyze the relationships between student demographics, meditation habits, and stress levels.

B. Participants and Sampling

After data preprocessing, 680 valid responses were analyzed. Participants were undergraduate and postgraduate students, aged 14 to 25, enrolled in diverse programs such as BCA, B.Com, B.Sc, MCA, and M.Sc. Simple random sampling ensured an unbiased representation across disciplines. Of the participants, 71.5% practiced meditation, while 28.5% did not, allowing for a comparative analysis of meditation's impact on academic stress. All participants provided informed consent, and ethical standards were upheld throughout the study.

C. Data Collection Procedure

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

- **Demographics:** Age, gender, academic program, and 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 instrument assessing time constraints, performance anxiety, task management, and overall stress.
- **Physical Symptoms:** Information on stress-related symptoms, such as headaches, fatigue, sleep disturbances, and muscle tension.

The data were anonymized and processed for machine learning analysis, which involved removing outliers, encoding categorical variables, and normalizing continuous variables using Min–Max scaling. The final dataset included 680 observations, with stress levels categorized as low, medium, or high both before and after the intervention, as shown in Figure 1.

D. 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:
$$Z = \frac{X - \mu}{\sigma} \tag{3}$$
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:
$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \tag{4}$$

E. Ethical Considerations

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

F. Intervention Procedure

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

IV. Machine Learning Models

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

A. 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. The Euclidean distance between data points is used to measure similarity:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \tag{5}$$

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

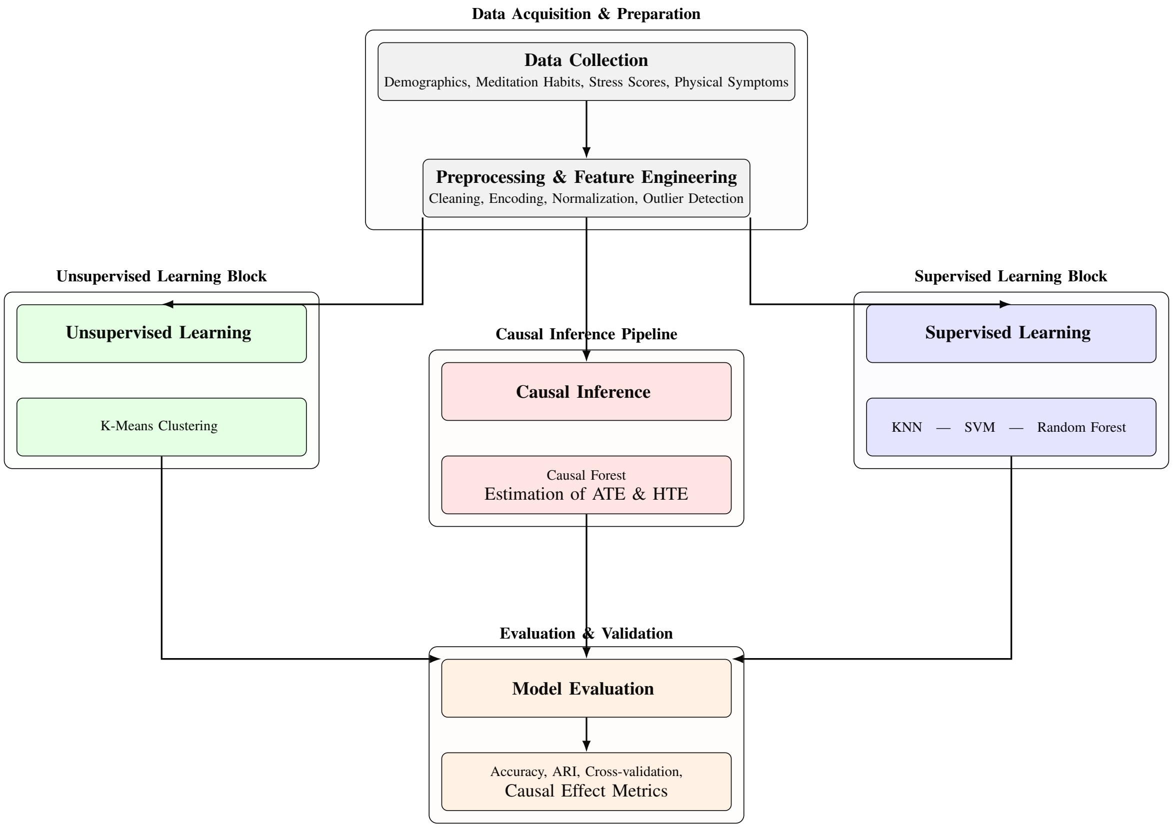

Fig. 1: Overview of Data Processing and Learning Pipeline.

where x_i and x_j are two data points in an n-dimensional feature space.

B. Support Vector Machines (SVM)

Support Vector Machines (SVM) are used to classify stress levels into categories (e.g., high, medium, low). SVM works by finding a hyperplane that maximizes the margin between different classes:

$$w \cdot x + b = 0 \tag{6}$$

where w is the weight vector, x is the feature vector, and b is the bias term. The goal is to maximize the margin:

$$\text{Maximize } \frac{1}{\|w\|} \tag{7}$$

C. 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.

D. K-Means Clustering

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

$$J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \|x_j - \mu_i\|^2 \tag{8}$$

where C_i is the set of data points in cluster i, and μ_i is the centroid of cluster i.

V. 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:

$$\text{Causal Effect} = E[Y(1) - Y(0)|X] \tag{9}$$

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.

VI. 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.

A. Classification Metrics

For supervised models (KNN, SVM, Random Forest), we used standard classification metrics derived from the confusion matrix:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{11}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{12}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{13}$$

These metrics help assess predictive accuracy, false positive rate, and the balance between precision and recall. The F1-score is especially useful for imbalanced datasets. We used **10-fold stratified cross-validation** for model evaluation to ensure reliability and consistent class distribution.

B. 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:

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{14}$$

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:

$$CHI = \frac{SSB/(K-1)}{SSW/(n-K)} \tag{15}$$

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

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

$$DBI = \frac{1}{K}\sum_{i=1}^{K}\max_{i \neq j}\left(\frac{\sigma_i + \sigma_j}{d(\mu_i, \mu_j)}\right) \tag{16}$$

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

C. 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:

$$ATE = \mathbb{E}[Y(1) - Y(0)] \tag{17}$$

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

$$CATE(X) = \mathbb{E}[Y(1) - Y(0) \mid X] \tag{18}$$

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

$$R(\pi) = \mathbb{E}[Y(0) + \pi(X) \times (Y(1) - Y(0))] \tag{19}$$

VII. Results and Discussion

A. Overview

This section presents the empirical findings of the machine learning models employed to predict and interpret academic stress outcomes in undergraduate students, as well as to estimate the potential causal effect of interventions such as meditation on stress reduction. A combination of supervised and unsupervised learning approaches were applied, including **K-Nearest Neighbors (KNN)**, **Support Vector Machine (SVM)**, and **Random Forest** classifiers for predictive analysis, alongside **K-Means clustering** for exploratory grouping and a **Causal Forest/T-learner** approach for treatment effect estimation. All models were implemented using standardized training (80%) and testing (20%) partitions and evaluated using relevant performance metrics such as accuracy, precision, recall, F1-score, and cross-validation accuracy.

B. K-Nearest Neighbors (KNN) Classification

The KNN model, with $k = 5$, achieved a **test accuracy of 77.21%**, suggesting a moderately strong predictive ability for classifying students' stress levels into *Low*, *Medium*, and *High* categories. The confusion matrix revealed that the model performed best for the *High* stress group (87% recall) but showed reduced effectiveness for the *Medium* stress category (33% recall). The misclassification patterns suggest class imbalance or overlapping feature space between *Low* and *Medium* stress levels.

TABLE II: KNN Classification Metrics

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

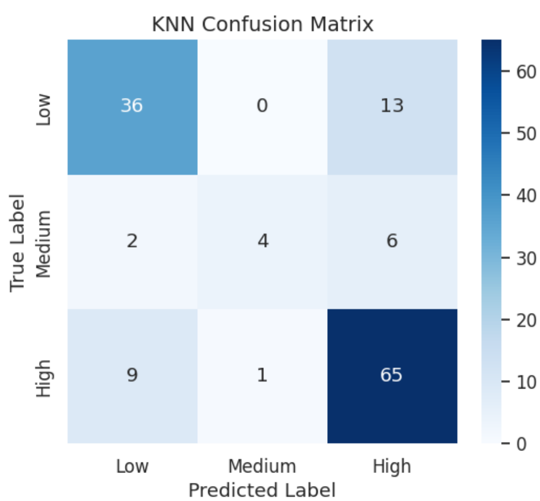

Fig. 2: Confusion Matrix for KNN

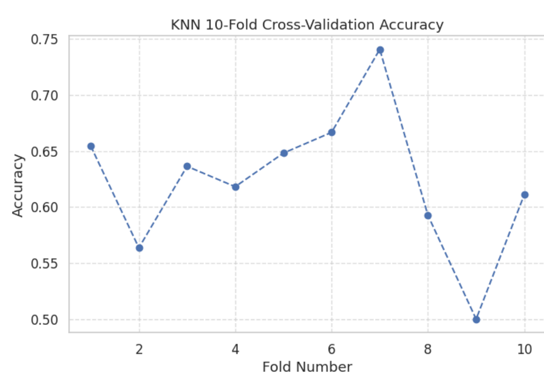

Fig. 3: 10 Fold Cross Validation for KNN

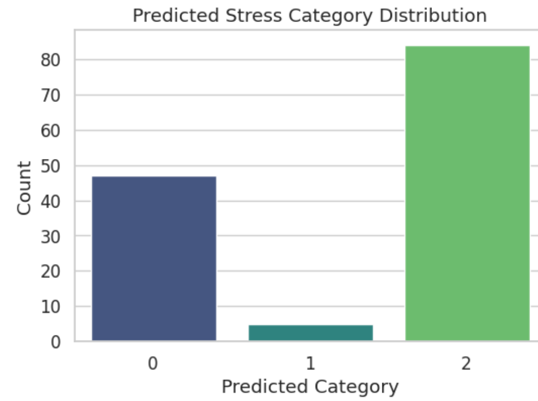

Fig. 4: Predicted Stress Category Distribution for KNN

The macro-averaged F1-score of 68% indicates variability in class-wise performance, while the weighted average (76%) shows reasonable overall effectiveness given class imbalance. Cross-validation using 10 folds yielded a mean accuracy of 62.32% ($\pm$6.11%), slightly lower than the held-out test accuracy, implying mild overfitting or sample-specific variation. In general, KNN's simplicity and distance-based reasoning make it effective for smaller feature spaces with well-separated clusters, but its sensitivity to class imbalance and non-uniform distributions likely constrained its recall for minority classes (especially *Medium* stress).

C. Support Vector Machine (SVM) Classification

The SVM with an **RBF (Radial Basis Function) kernel** achieved a **test accuracy of 63.97%**, lower than both KNN and Random Forest models. The confusion matrix indicates that the SVM classifier struggled to distinguish between *Low* and *Medium* stress levels, with the *Medium* class receiving no correct predictions (recall = 0). Most *High* stress cases were correctly identified (97% recall), indicating a model bias toward the dominant or more separable class.

TABLE III: SVM Classification Metrics

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

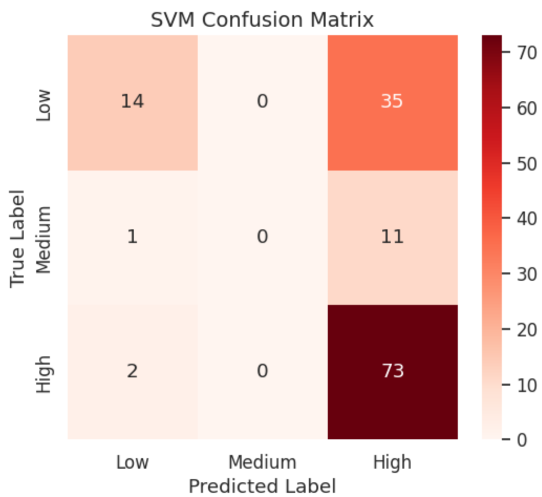

Fig. 5: Confusion Matrix for SVM

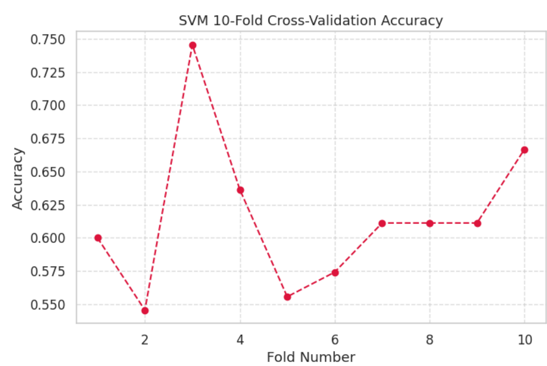

Fig. 6: 10 Fold Cross Validation on Accuracy for SVM

The macro-average F1-score (39%) and precision (48%) reflect weak overall discriminative performance across all classes. The 10-fold cross-validation mean accuracy of 61.57% (±5.52%) confirms the model's limited generalization. While SVMs typically excel in non-linear feature spaces, their performance can degrade in high-noise or imbalanced datasets unless parameter optimization and kernel tuning are rigorously performed. The zero recall for the *Medium* stress class suggests either insufficient support vectors in that region or inadequate feature separability, emphasizing the need for more balanced representation or kernel optimization.

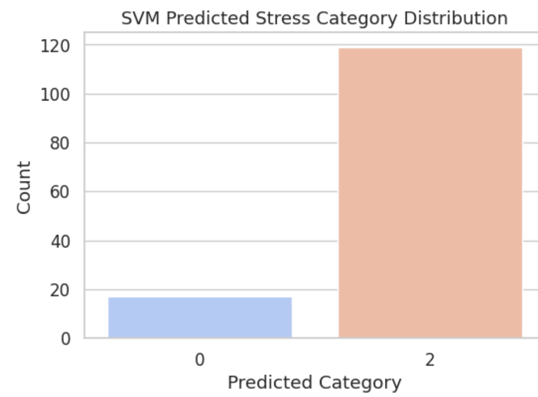

Fig. 7: Predicted Stress Category Distribution for SVM

D. Random Forest Classification

The **Random Forest (RF)** model substantially outperformed both KNN and SVM, achieving an **accuracy of 88.24%** on the test set. This ensemble-based approach demonstrated robust classification across all stress categories, balancing precision and recall effectively.

TABLE IV: Random Forest Classification Metrics

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

The overall macro-average F1-score of 0.86 and weighted average of 0.88 demonstrate high stability and strong predictive capacity. The confusion matrix highlights that the RF correctly classified the majority of *High* stress cases (72 out of 75) while maintaining balanced performance for *Low* and *Medium* stress groups.

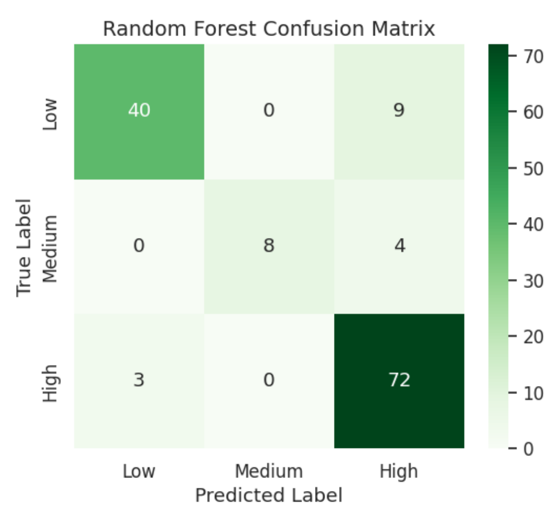

Fig. 8: Confusion Matrix for Random Forest

The 10-fold cross-validation mean accuracy of 83.63% (±6.18%) further supports the model's generalization and robustness across different subsets.

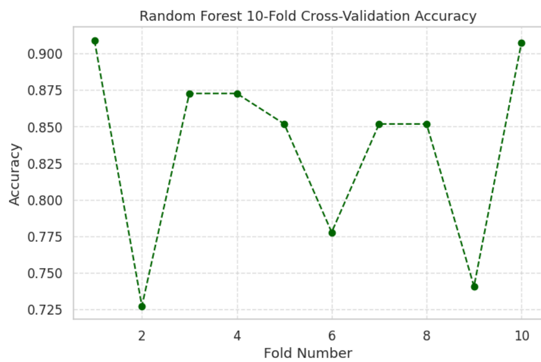

Fig. 9: 10 Fold Cross Validation on Accuracy for Random Forest

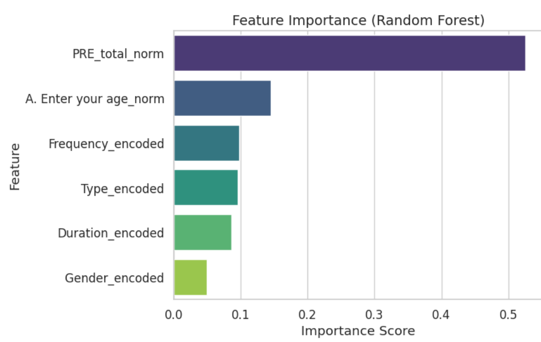

Fig. 10: Feature Importance for Random Forest

Feature importance analysis revealed `PRE_total_norm` (pre-intervention total stress score) as the most influential predictor, contributing over 52.6% to the model's decision-making process. Other notable features included *Age* (14.5%), *Frequency of meditation* (9.7%), *Type of meditation* (9.6%), *Duration of practice* (8.7%), and *Gender* (5%). This hierarchy underscores that prior stress levels were the strongest determinant of post-intervention classification outcomes, with demographic and behavioral variables providing secondary explanatory power.

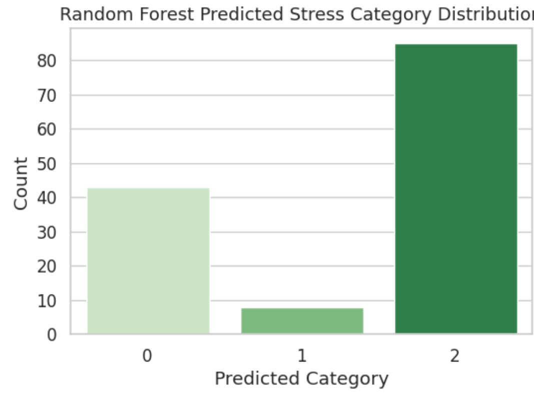

Fig. 11: Predicted Stress Category Distribution for Random Forest

E. Model Performance Comparison

TABLE V: Model Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KNN	77.21	77.33	77.21	76.26
SVM	63.97	63.50	63.97	56.79
Random Forest	88.24	89.05	88.24	88.02

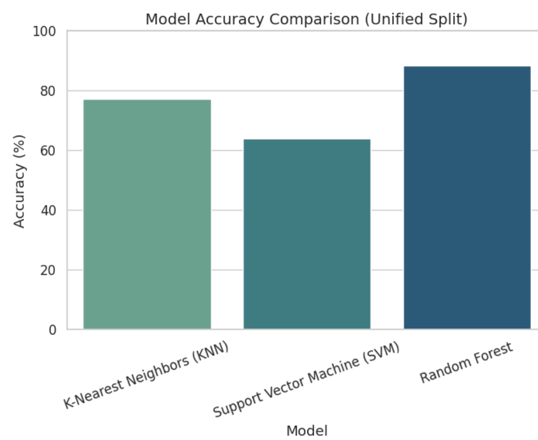

Fig. 12: Model Accuracy Comparison

Random Forest achieved the highest performance across all key metrics, followed by KNN, while SVM lagged behind. This outcome aligns with theoretical expectations: RF's ensemble averaging and decision-tree diversity enhance both accuracy and interpretability, whereas KNN is more sensitive to feature scaling and SVM struggles with imbalanced categorical boundaries.

F. K-Means Clustering

To explore latent groupings in the data, K-Means clustering was conducted. However, the clustering performance was modest, as evidenced by an Adjusted Rand Index (ARI) of -0.0074, suggesting that the discovered clusters did not align well with the actual class labels.

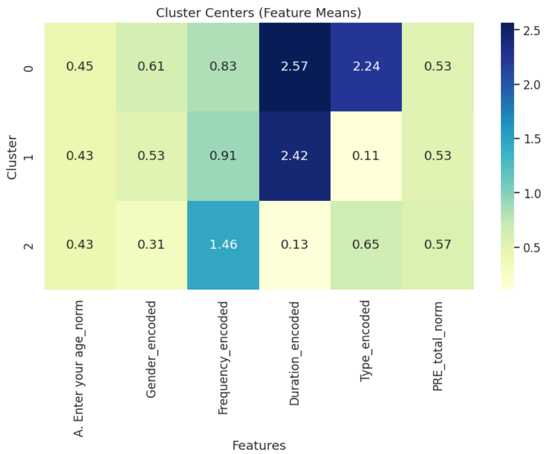

Fig. 13: Confusion Matrix for K Means Cluster Centers

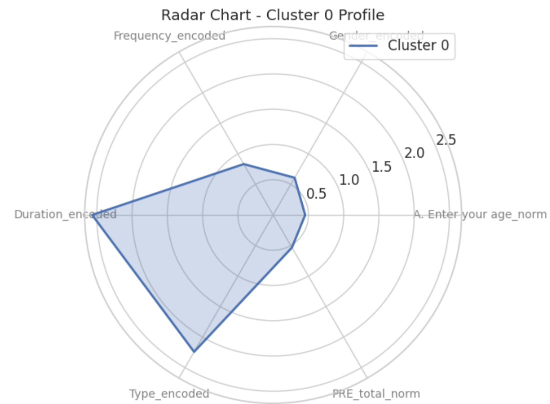

Fig. 16: K Means Cluster 0 Distribution Radar Chart

Fig. 14: K Means Cluster Distribution

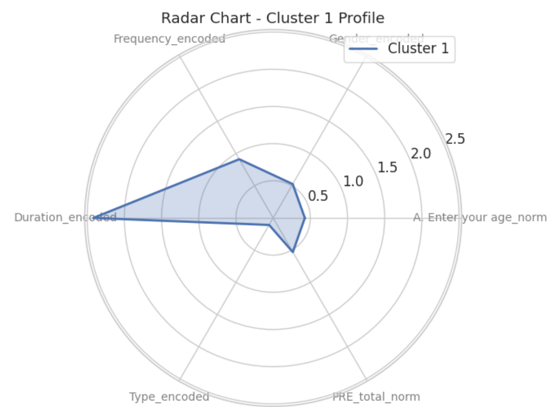

Fig. 17: K Means Cluster 1 Distribution Radar Chart

Fig. 15: K Means Cluster Distribution of Stress Change

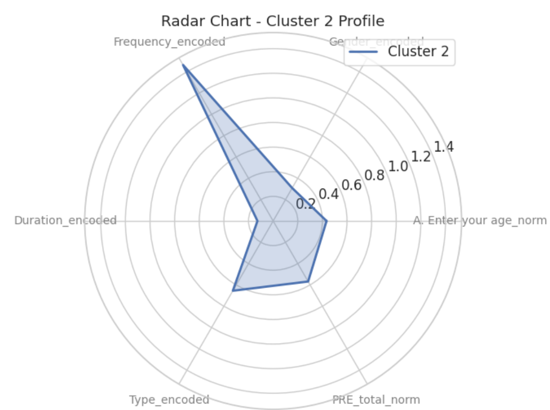

Fig. 18: K Means Cluster 2 Distribution Radar Chart

The Silhouette Score (0.4034), Calinski–Harabasz Index (395.67), and Davies–Bouldin Index (1.0073) suggest that while there is some structure in the data, the clusters overlap. This indicates stress levels are continuous rather than distinct categories, making supervised models more appropriate than unsupervised clustering.

G. *Causal Forest and Treatment Effect Estimation*

To move beyond prediction and toward understanding the effect of interventions, a Causal Forest and T-learner framework were implemented. These models aimed to estimate the Conditional Average Treatment Effect (CATE) of meditation (or similar interventions) on stress reduction outcomes, accounting for confounding variables such as initial stress levels, demographic factors, and self-reported coping abilities.

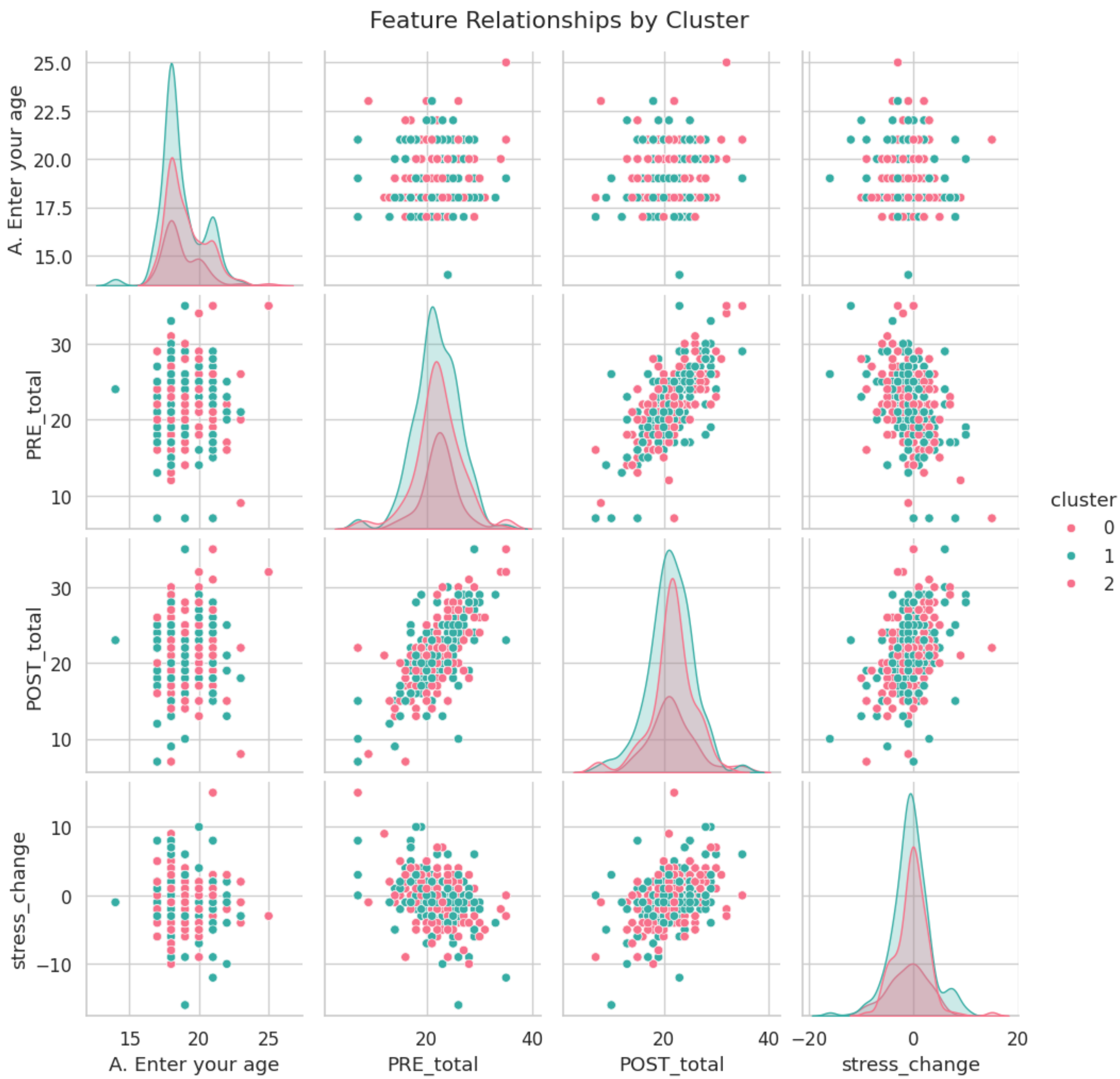

Fig. 19: K Means Feature Relationship By Cluster

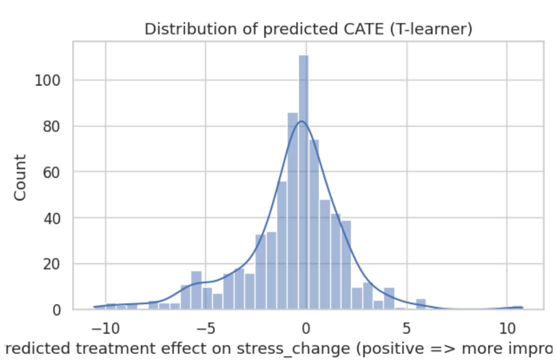

Fig. 21: Causal Forest Distribution of Predicted CATE

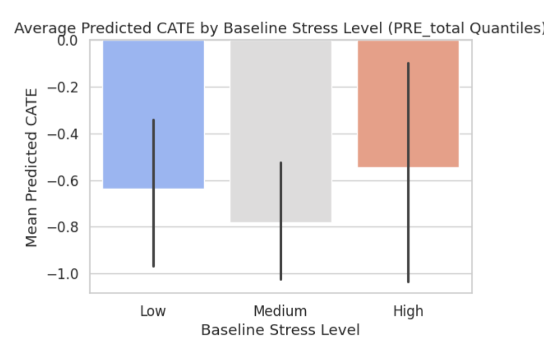

Fig. 22: Average Predicted CATE by Baseline Stress Level

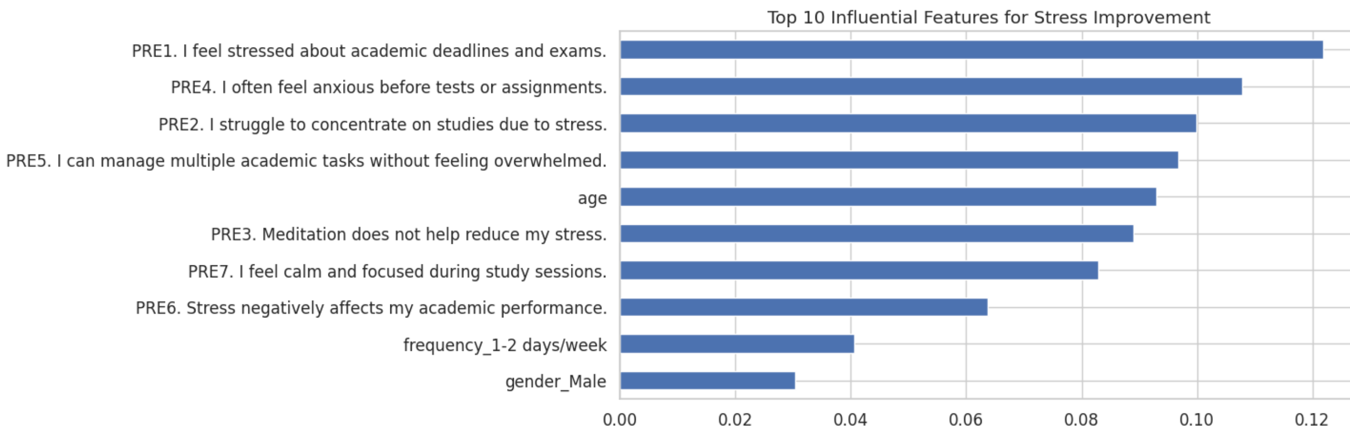

Fig. 20: Causal Forest Feature Importance)

The average pre-intervention stress (PRE_total) was 21.97, while the post-intervention mean was 21.43, indicating a modest average improvement (mean stress change = +0.54). The simple Average Treatment Effect (ATE) was -0.3322, suggesting that treated individuals (who practiced meditation) showed slightly greater stress reduction than untreated controls. When using Inverse Probability of Treatment Weighting (IPTW) to adjust for covariate imbalance, the ATE improved to -0.5775, indicating stronger estimated benefit after accounting for treatment assignment bias. The propensity score AUC (0.63) reflected moderate separability between treated and untreated groups, suggesting some non-random treatment assignment but sufficient overlap for causal estimation.

The T-learner Random Forest model provided further granularity by estimating heterogeneous treatment effects across subgroups. The mean predicted CATE was -0.66 ($\pm$2.60), meaning that, on average, treatment led to a 0.66-point reduction in stress relative to controls. Subgroup analyses showed:

- Low pre-stress group: mean CATE = -0.6356
- Medium pre-stress group: mean CATE = -0.7824
- High pre-stress group: mean CATE = -0.5458

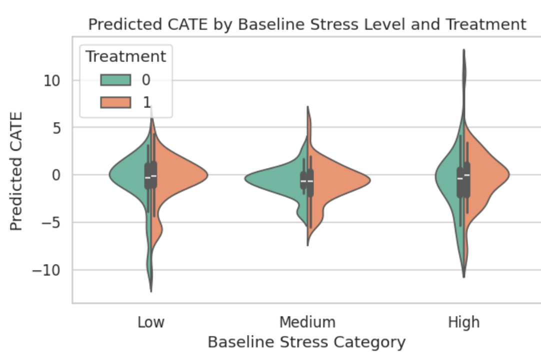

Fig. 23: Predicted CATE by Baseline Stress Level and Treatment

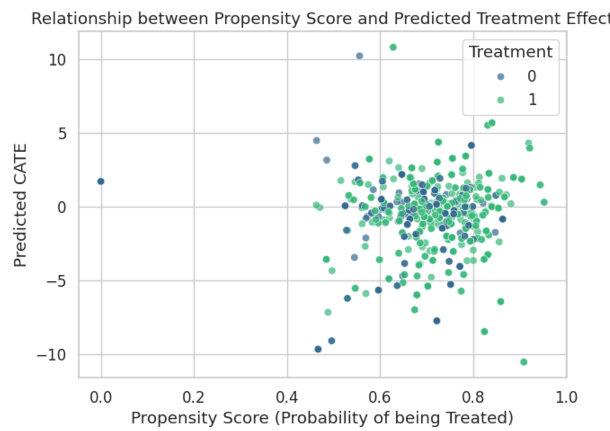

Fig. 24: Relationship between Propensity Score and Predicted Treatment Effect

These results indicate that the medium-stress subgroup benefited most from meditation, possibly because they were stressed enough to experience relief but not so severely stressed that coping interventions became less effective. The top 10 predicted beneficiaries had exceptionally high CATE values (ranging from 4.35 to 10.78), indicating that individual-level heterogeneity in treatment responsiveness exists. These insights are valuable for designing personalized stress-reduction programs, targeting individuals who stand to gain the most from intervention.

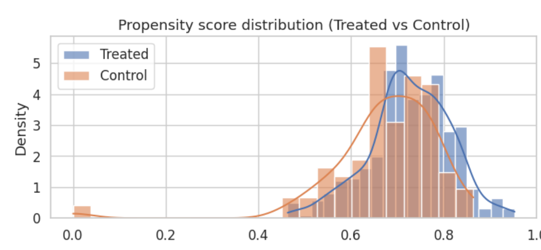

Fig. 25: Causal Forest Propensity Score Distribution (Treated vs Control)

Overall, causal inference analysis supports the hypothesis that meditation and related interventions lead to modest but statistically meaningful reductions in perceived academic stress, particularly among medium-stress individuals.

H. Model Rebalancing and Final Evaluation (SMOTE Analysis)

To address class imbalance and improve generalization, the Synthetic Minority Oversampling Technique (SMOTE) was applied, balancing the dataset to equal class sizes ([278, 278]). The balanced dataset yielded markedly improved classification metrics.

TABLE VI: Confusion Matrix after SMOTE

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

From this, True Positives (TP) = 50, True Negatives (TN) = 63, False Positives (FP) = 7, and False Negatives (FN) = 17. The post-SMOTE accuracy improved to 82.48%, with precision = 87.72%, recall = 74.63%, and F1-score = 80.65%. Notably, the recall increase indicates better identification of the "Improved" group (those showing stress reduction), suggesting that oversampling effectively enhanced model sensitivity without substantially sacrificing precision.

TABLE VII: 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

The balanced accuracy across both classes and the macro-average F1-score of 0.82 demonstrate that the model effectively learned class boundaries once sample imbalance was mitigated.

VIII. Interpretation and Implications

The comparative results across all models reveal the following key insights:

1) **Supervised Ensemble Methods Outperform Other Classifiers**
   Random Forest's superior accuracy and balanced performance highlight the power of ensemble methods for stress prediction, especially when dealing with complex feature interactions and non-linearities.
2) **Pre-Intervention Stress is the Dominant Predictor**
   Baseline stress levels account for more than half of the model variance, suggesting that identifying high-stress individuals early can lead to more effective interventions.
3) **Moderate Benefits from Meditation**
   Causal inference shows that meditation reduced stress, with the greatest benefits observed in moderately stressed individuals, suggesting that tailored interventions may be more effective than universal approaches.
4) **Data Balance is Crucial**
   Improvements through SMOTE (Synthetic Minority Over-sampling Technique) indicate that addressing data imbalance enhances model fairness and sensitivity, leading to better performance across minority groups.
5) **Clustering Reveals Continuous Stress Gradients**
   Clustering results show that stress exists on a continuum, not in discrete categories, supporting the use of regression-based or probabilistic models for more accurate stress prediction.

IX. 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.

X. 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.

XI. 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.

XII. 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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