MACHINE LEARNING - BASED FEASIBILITY ANALYSIS OF AYURVEDIC PRAKRITI CLASSIFICATION USING PSYCHOLOGICAL AND LIFESTYLE INDICATORS

Abstract

Machine learning has been widely applied to psychological and behavioral data; however, its use in traditional medical systems such as Ayurveda remains limited, particularly when restricted to non-physiological features. This study evaluates the feasibility of classifying Ayurvedic Prakriti types using only psychological well-being, lifestyle, and human-need indicators. A publicly available dataset comprising 500 samples was used, including features such as stress level, anxiety and depression scores, Maslow's hierarchy of needs, sleep duration, exercise frequency, caffeine intake, and screen time. Prakriti classification was formulated as a multiclass problem and examined using three classical machine learning models: Logistic Regression, Support Vector Machine, and Random Forest. Models were trained and evaluated using a stratified 80–20 train–test split, with performance assessed through accuracy and macro-averaged F1-score. Across models, classification performance remained low, with accuracy ranging from 13% to 22%, only marginally above chance level for the given number of classes. Logistic Regression and Support Vector Machine consistently outperformed Random Forest, though none achieved reliable discriminative performance, indicating substantial overlap among Prakriti categories when represented solely through psychological and lifestyle variables. These findings suggest that such features, as currently measured, are insufficient for accurate Prakriti classification. Rather than demonstrating predictive success, this study provides a systematic feasibility assessment highlighting key limitations of psychological-only approaches and reinforcing the need for multi-modal data integration, particularly physiological and expert-annotated indicators, in future computational Ayurveda research.

Introduction

Psychological well-being is shaped by interacting emotional, behavioral, and lifestyle factors, including stress, anxiety, sleep quality, physical activity, dietary habits, and digital screen exposure. These variables have been repeatedly linked to mental health outcomes and quality of life, particularly in questionnaire-based psychological research [1], [2]. The increasing availability of large-scale psychological and lifestyle datasets has enabled the use of computational methods to analyze such complex interactions, especially where traditional statistical approaches struggle to model non-linear and high-dimensional relationships [3].

Machine learning (ML) methods have therefore become prominent in psychological and behavioral research, where they have been applied to tasks such as predicting mental health conditions, estimating stress and anxiety levels, and examining behavioral patterns associated with sleep, exercise, and technology use [4], [5]. These studies demonstrate that ML can effectively capture complex associations in self-reported psychological data. However, most existing work is grounded in contemporary biomedical or psychological frameworks, and relatively few studies have examined whether similar approaches are applicable to traditional medical systems with holistic and culturally specific foundations.

Ayurveda, one of the world's oldest systems of medicine, conceptualizes individual differences through the notion of *Prakriti*, an innate psychosomatic constitution believed to influence physical health, emotional tendencies, cognition, and behavior across the lifespan [6]. Psychological characteristics are considered integral to Prakriti assessment, making them a theoretically relevant input for computational analysis. In practice, however, Prakriti determination relies largely on qualitative evaluations by Ayurvedic practitioners, which introduces subjectivity and limits scalability, reproducibility, and systematic validation.

While several computational studies have explored Prakriti classification using machine learning, most emphasize physiological or physical attributes such as body composition, pulse diagnosis, or biochemical markers [7]. Psychological and lifestyle indicators are comparatively underrepresented. Furthermore, existing approaches often prioritize predictive accuracy without adequately addressing challenges such as class overlap, dataset imbalance, limited sample sizes, and the interpretability of models applied to holistic human profiling [8]. As a result, it remains unclear whether psychological and lifestyle data alone contain sufficient discriminative information to support reliable Prakriti classification.

To address this gap, the present study conducts a feasibility analysis of Prakriti classification using only psychological well-being measures, lifestyle factors, and human-need indicators. Specifically, we investigate:

(1) whether classical machine learning models can distinguish Prakriti types using psychological and lifestyle features alone;

(2) how different model architectures compare under these constraints; and

(3) what limitations emerge when physiological data are excluded.

Logistic Regression, Support Vector Machine (SVM), and Random Forest classifiers were selected to represent models of increasing complexity and were evaluated in a multiclass setting using a dataset of 500 samples. Given the holistic and stable nature of Prakriti, we hypothesized that psychological and lifestyle indicators alone would yield limited predictive performance, thereby serving as a baseline assessment rather than an optimized classification solution. Rather than emphasizing predictive success, this study aims to provide a realistic evaluation of the applicability and limitations of machine learning in computational Ayurveda, offering insights to guide future multi-modal and interdisciplinary research.

Literature Review

Recent years have seen growing interest in applying machine learning (ML) techniques to Ayurvedic knowledge systems, motivated by the challenge of translating traditionally qualitative and experience-driven concepts into computationally analyzable forms [1], [2]. Central to this effort is *Prakriti*, an individual's innate psychosomatic constitution that informs personalized diagnosis and treatment in Ayurveda [3]. While conceptually rich, Prakriti assessment is inherently complex, as it integrates physical, psychological, and behavioral dimensions and is traditionally determined through qualitative practitioner judgment. This complexity poses significant challenges for empirical modeling and motivates the exploration of ML-based approaches.

A substantial portion of existing work frames Prakriti identification as a supervised multiclass classification problem using questionnaire-derived data. These studies commonly rely on structured surveys or digitized Ayurvedic textual sources and emphasize extensive preprocessing to reduce semantic variability. Techniques such as ontology mapping, term normalization, named entity recognition, and vector-space representations (e.g., TF–IDF with cosine similarity) are frequently employed, particularly in text-based datasets [4], [5]. While such pipelines improve data consistency, multiple studies note that the absence of standardized, large-scale Ayurvedic datasets remains a critical limitation, restricting reproducibility and cross-study comparison.

Across standardized datasets, a wide range of classical ML models has been evaluated, including Logistic Regression, Support Vector Machines (SVM), Naïve Bayes, Decision Trees, and k-Nearest Neighbors [6]. More recent work increasingly reports ensemble-based methods such as Random Forest, AdaBoost, XGBoost, and CatBoost, citing their ability to model non-linear relationships and mitigate class imbalance [7]. Reported classification accuracies in these studies typically range from approximately 58% to 82%, particularly when physiological or physical attributes—such as body composition, pulse diagnosis, or biochemical indicators—are included. However, these performance gains are often accompanied by aggressive preprocessing, resampling strategies, or feature engineering pipelines that may limit interpretability and generalizability.

A parallel research stream explores the incorporation of modern psychometric constructs into computational Ayurveda. Variables such as intelligence quotient, emotional quotient, personality traits, and risk-taking behavior have been examined as correlates of dosha dominance [8]. Tree-based ensemble models combined with explainability tools, particularly SHAP-based feature attribution, are commonly employed to identify psychologically meaningful predictors. While these studies report interpretable associations between psychological traits and Prakriti categories, authors consistently caution that findings are constrained by self-reported data, limited sample sizes, and population homogeneity, raising concerns about robustness.

Lifestyle and behavioral factors—including stress, sleep duration, physical activity, caffeine intake, and digital screen exposure—are frequently acknowledged in conceptual and review-oriented studies as integral to Prakriti assessment [9]. Despite this recognition, such variables are often underrepresented in computational models or treated as secondary features. The literature repeatedly highlights the scarcity of large, labeled lifestyle datasets suitable for ML applications, resulting in models that capture only a partial representation of Ayurveda's holistic framework.

Interpretability emerges as a central concern across nearly all ML-based Ayurvedic studies. Several authors argue that earlier work prioritized predictive accuracy at the expense of transparency, thereby limiting clinical relevance and practitioner trust [8], [10]. Black-box models, particularly deep neural networks, are often viewed as misaligned with Ayurvedic diagnostic philosophy, which emphasizes explicit reasoning and theoretical grounding. Consequently, classical ML models and interpretable ensemble methods are frequently favored, even when they offer lower predictive performance.

Despite steady methodological progress, persistent challenges remain. Most datasets rely on self-reported questionnaires, introducing subjective bias and measurement error. Sample sizes are typically modest, class distributions are often highly imbalanced, and cultural homogeneity limits external validity. Moreover, few studies explicitly examine the feasibility of Prakriti classification when physiological features are excluded, leaving open the question of whether psychological and lifestyle indicators alone provide sufficient discriminative information.

In summary, existing research demonstrates that machine learning can support Prakriti classification when multi-modal and physiologically rich data are available. However, three critical gaps remain: (1) limited investigation of psychological and lifestyle features in isolation, (2) an emphasis on optimized accuracy rather than feasibility and failure analysis, and (3) insufficient reporting of negative or near-chance results. The present study addresses these gaps by conducting a feasibility-oriented and comparative evaluation of classical ML models using only psychological well-being, lifestyle, and human-need indicators, with an emphasis on realistic performance assessment and methodological transparency.

Methodology

Dataset Description

The dataset used in this study was obtained from a publicly available Kaggle repository titled *"Treatment for Psychology Patients Using Ayurveda"* (/kaggle/input/treatment-for-psychology-patients-using-ayurveda). It comprises **500 individual participant records** and includes psychological, lifestyle, and human-need indicators relevant to Ayurvedic Prakriti assessment.

The dataset contains **13 independent features**: age, stress level, anxiety level, depression score, sleep duration, exercise frequency, caffeine intake, daily screen time, and quantified measures corresponding to Maslow's hierarchy of needs (physiological, safety, social, esteem, and self-actualization). The **target variable** corresponds to the **Ayurvedic Prakriti type**, representing one of **six classes**: Kapha, Pitta, Pitta-Kapha, Vata, Vata-Kapha, and Vata-Pitta. The class distribution in the dataset is summarized in Table 1a.

Table 1a: Prakriti Class Distribution

Prakriti Type	**Training Set**	**Test Set**	**Total**
Kapha	72	18	90
Pitta	72	18	90
Pitta-Kapha	68	17	85
Vata	56	14	70
Vata-Kapha	68	17	85
Vata-Pitta	64	16	80
Total	400	100	500

The **Prakriti labels were obtained using a structured questionnaire based on Ayurvedic principles**, which introduces potential subjective bias and may limit reproducibility.

Data Preprocessing

Prior to training, the dataset underwent standard preprocessing to ensure consistency and suitability for supervised learning. Missing data was minimal, with no feature containing more than three missing values; all records were retained. All features were numerical, eliminating the need for categorical encoding.

Feature distributions were checked for outliers and inappropriate ranges. Given the bounded nature of psychological and lifestyle scores, no extreme outliers were removed. Feature scaling was performed using **standardization** to normalize the range of input variables:

$$x' = \frac{x - \mu}{\sigma}$$

where $x'$is the scaled feature, $x$is the original value, $\mu$is the mean, and $\sigma$is the standard deviation. Standardization ensured that algorithms sensitive to feature magnitude, such as Logistic Regression and Support Vector Machine, were not biased by differing scales.

No dimensionality reduction or automated feature selection was applied due to the moderate number of features and their conceptual relevance.

Feature Set and Target Variable Definition

The independent feature set Xincludes all 13 psychological, lifestyle, and human-need variables. The dependent target variable $y$represents the Prakriti class for each participant. The classification problem is formally expressed as:

$$X \mapsto y, y \in \{\text{Kapha, Pitta, Pitta-Kapha, Vata, Vata-Kapha, Vata-Pitta}\}$$

The goal was to evaluate feasibility and comparative performance of classical machine learning models without discarding features of theoretical importance.

Train–Test Split Strategy

To evaluate generalization and prevent overfitting, the dataset was split into training and testing sets using an **80:20 stratified split**, ensuring the original Prakriti class distribution was preserved. A **fixed random seed** was used for reproducibility:

$$X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train\_test\_split}(X, y, test\_size = 0.2, stratify = y, random\_state = 42)$$

- Training set: 400 samples
- Test set: 100 samples

Machine Learning Models

Three classical supervised learning algorithms were employed to evaluate the feasibility of classifying Ayurvedic Prakriti types: **Logistic Regression**, **Support Vector Machine (SVM)**, and **Random Forest**. These models were selected due to their widespread use in healthcare and psychological data analysis, varying complexity levels, and relative interpretability. All models were trained on the 400-sample training set and evaluated on the 100-sample test set.

1. Logistic Regression

Logistic Regression is a **linear classification algorithm** that models the probability of a sample belonging to a particular class using the logistic function. For multiclass classification, the **one-vs-rest** strategy was employed, where a separate binary classifier is trained for each Prakriti class against all others.

The probability of a sample $x = [x_1, x_2, \ldots, x_n]$belonging to class $k$is given by the **softmax function**:

$$P(y = k \mid x) = \frac{e^{\beta_{0,k} + \sum_{i=1}^{n} \beta_{i,k} x_i}}{\sum_{j=1}^{K} e^{\beta_{0,j} + \sum_{i=1}^{n} \beta_{i,j} x_i}}$$

where:

- $K = 6$is the number of Prakriti classes,
- $\beta_{0,k}$is the intercept for class k,
- $\beta_{i,k}$is the coefficient for feature $x_i$for class k.

The **decision rule** assigns the class with the highest probability:

$$\hat{y} = \arg\max_{k} P(y = k \mid x)$$

Hyperparameters used:

- Solver: lbfgs
- Multiclass: one-vs-rest
- Regularization parameter: $C = 1.0$
- Maximum iterations: max_iter=100

Logistic Regression was chosen for its simplicity, computational efficiency, and interpretability, allowing a direct understanding of feature influence on Prakriti prediction.

2. Support Vector Machine (SVM)

SVM is a **discriminative classifier** that finds an optimal hyperplane to separate data points in a high-dimensional feature space. The **RBF (Radial Basis Function) kernel** was used to capture potential nonlinear relationships.

For a binary SVM, the optimization problem is formulated as:

$$\min_{w,b} \frac{1}{2} \| w \|^2 + C \sum_{j=1}^{m} \xi_j$$

subject to:

$$y_j(w \cdot \phi(x_j) + b) \geq 1 - \xi_j, \xi_j \geq 0$$

where:

- $w$is the weight vector,
- $b$is the bias term,
- $\phi(x_j)$is the kernel transformation of the input feature x_j,
- $y_j \in \{-1,1\}$is the label,
- $\xi_j$are slack variables for soft-margin classification,
- $C = 1.0$is the regularization parameter controlling margin violation.

The **RBF kernel** is defined as:

$$K(x_i, x_j) = \exp\left(\quad -\gamma \| x_i - x_j \|^2 \right)$$

with $\gamma =$ ’scale’(1 / (n_features × X.var())) in scikit-learn.

Hyperparameters used:

- Kernel: RBF
- C: 1.0
- Gamma: 'scale'
- Multiclass handled via one-vs-rest strategy

SVM was included to evaluate its capability to model nonlinear separability among psychological, lifestyle, and Prakriti features.

3. Random Forest

Random Forest is an **ensemble method** that builds multiple decision trees on random subsets of the training data and features, aggregating predictions via **majority voting**. Each tree $h_t(x)$makes a prediction, and the final class $\hat{y}$is:

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \ldots, h_T(x)\}$$

where $T = 100$is the total number of trees. Each tree uses a random subset of features at each split to reduce correlation and overfitting.

Hyperparameters used:

- Number of trees (n_estimators) = 100
- Maximum tree depth (max_depth) = None (nodes expanded until all leaves are pure)
- Minimum samples per split (min_samples_split) = 2
- Random state = 42 for reproducibility

Random Forest was chosen for its ability to model **complex nonlinear feature interactions** and for providing some interpretability through feature importance metrics.

Experiments and Results

Experimental Setup

The experimental phase of this study was designed to evaluate the **feasibility of classifying Ayurvedic Prakriti types** using psychological well-being measures, lifestyle variables, and human-need indicators through classical machine learning models. The study emphasizes a transparent, controlled, and comparative assessment of model behavior rather than maximizing predictive performance.

The preprocessed dataset consisted of **500 participant samples**, each representing a unique profile with 13 numerical features. The dataset includes six Prakriti classes:

1. Kapha
2. Pitta
3. Pitta-Kapha
4. Vata

5. Vata-Kapha
6. Vata-Pitta

The **chance-level accuracy** for a uniform random classifier is:

$$\text{Chance Accuracy} = \frac{1}{K} = \frac{1}{6} \approx 0.167\ (16.7\%)$$

To evaluate model generalization and prevent overfitting, the dataset was split into training and testing sets using an **80:20 stratified split**:

$$X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train\_test\_split}(X, y, \text{test\_size} = 0.2, \text{stratify} = y, \text{random\_state} = 42)$$

- **Training set:** 400 samples
- **Testing set:** 100 samples

Stratification ensured that each Prakriti category was proportionally represented in both subsets, maintaining class distribution for a fair multiclass evaluation.

Three supervised models were employed:

1. **Logistic Regression (LR)** – linear model modeling class probabilities via the softmax function.
   - Hyperparameters: solver='lbfgs', C=1.0, max_iter=100, multi_class='ovr'
2. **Support Vector Machine (SVM)** – RBF kernel SVM for margin-based nonlinear classification.
   - Hyperparameters: kernel='rbf', C=1.0, gamma='scale'
3. **Random Forest (RF)** – ensemble of decision trees aggregating predictions via majority voting.
   - Hyperparameters: n_estimators=100, max_depth=None, min_samples_split=2

All models were trained on **standardized features**, where each feature $x_i$was scaled as:

$$x_i' = \frac{x_i - \mu_i}{\sigma_i}$$

- x_i'= scaled feature value
- μ_i= mean of feature i
- σ_i= standard deviation of feature i

Evaluation Metrics

1. Accuracy: Measures the proportion of correctly classified samples:

$$\text{Accuracy} = \frac{\sum_{i=1}^{N} \mathbf{1}(\hat{y}_i = y_i)}{N}$$

- N= total number of test samples
- $\hat{y}_i$= predicted class for sample i
- y_i= true class label

2. F1-score (macro-averaged): Balances precision and recall across all classes:

$$\text{Precision}_k = \frac{\text{TP}_k}{\text{TP}_k + \text{FP}_k}, \text{Recall}_k = \frac{\text{TP}_k}{\text{TP}_k + \text{FN}_k}$$

$$\text{F1-score}_k = 2 \cdot \frac{\text{Precision}_k \cdot \text{Recall}_k}{\text{Precision}_k + \text{Recall}_k}, \text{F1-score}_{\text{macro}} = \frac{1}{K}\sum_{k=1}^{K} \text{F1-score}_k$$

These metrics account for potential class imbalance and provide a detailed view of model performance in multiclass Prakriti classification.

Model Performance Results

The test set performance of the three models is summarized in **Table 1**, alongside the chance-level baseline for reference.

Model	**Accuracy**	**Macro-Averaged F1-score**
Logistic Regression	0.22	0.22
Support Vector Machine	0.22	0.22

Model	Accuracy	Macro-Averaged F1-score
Random Forest	0.13	0.12
Chance Baseline (K=6)	0.167	—

Table 1: Overall classification performance on the test set (N=100). Chance baseline represents uniform random classification.

- **Logistic Regression and SVM** achieved identical performance (0.22), slightly above chance, suggesting the presence of some global linear trends.
- **Random Forest** performed worse (0.13), likely due to **moderate sample size, class overlap, and noisy self-reported features**.

The results highlight the inherent challenge of Prakriti classification using only psychological, lifestyle, and human-need indicators, validating the study's **feasibility-focused approach**.

Result Analysis

The overall classification performance observed across all models was modest, reflecting the inherent difficulty of **multiclass Prakriti classification** when relying solely on psychological well-being, lifestyle, and human-need indicators. Accuracy values ranged from **13% to 22%**, which is near the **chance-level accuracy of 16.7%** for six classes ($K = 6$):

$$\text{Chance Accuracy} = \frac{1}{K} = \frac{1}{6} \approx 0.167$$

This indicates that the discriminative information contained in the chosen feature set is limited for reliably distinguishing among Prakriti categories.

Linear vs Nonlinear Patterns: Logistic Regression and Support Vector Machine achieved comparable performance (accuracy = 0.22, F1-score = 0.22), slightly above chance. This suggests that the separable patterns in the dataset are largely **linear or approximately linear**, and that introducing model complexity beyond linear or margin-based classifiers (e.g., Random Forest) did not yield substantial gains. In other words, the psychological and lifestyle features alone do not contain sufficient nonlinear relationships that more complex models could exploit effectively.

Random Forest Performance: Random Forest, designed to capture nonlinear feature interactions, exhibited the lowest performance (accuracy = 0.13, F1-score = 0.12). This reduced performance can be attributed to several factors:

1. **Moderate dataset size (N=500)** limiting the ability to learn robust decision boundaries.
2. **Limited feature dimensionality (13 features)**, constraining the model's capacity to identify complex interactions.
3. **High inter-class similarity**, as evident from the Random Forest classification report, where mixed Prakriti categories (e.g., Vata-Pitta, Pitta-Kapha) frequently experienced misclassification.

Class-level observations reinforce these trends:

- Classes such as **Pitta-Kapha** and **Vata-Kapha** achieved slightly higher recall (≈0.22–0.24), indicating that certain patterns in psychological and lifestyle indicators are somewhat distinctive for these constitutions.
- Classes like **Vata-Pitta** and **Kapha** consistently showed low recall (≈0.0–0.06), highlighting substantial overlap with other Prakriti types.

These outcomes align with **Ayurvedic theory**, where mixed constitutions are common and may not exhibit sharply separable characteristics. The reliance on **self-reported measures** further contributes to noise and variability in the feature space, reducing the separability of Prakriti classes.

Interpretational Insights:

- The low accuracy and F1-scores across all models do not indicate a failure of machine learning per se, but rather the **conceptual and methodological constraints** of the dataset.
- Prakriti is a **multidimensional, holistic construct**, influenced by physiological, psychological, behavioral, and environmental factors. Without physiological or clinical data, the current feature set only partially represents the full spectrum of constitutional attributes.
- From a **feasibility standpoint**, these results demonstrate that while machine learning can detect limited trends in psychological and lifestyle indicators, these features alone are insufficient for robust Prakriti classification.

$$\text{F1-score}_{\text{macro}} = \frac{1}{K}\sum_{k=1}^{K}\frac{2\cdot \text{Precision}_k \cdot \text{Recall}_k}{\text{Precision}_k + \text{Recall}_k}$$

Overall, the findings underscore the necessity of:

1. **Richer, multimodal datasets**, integrating physiological, behavioral, and clinical variables.
2. **Interdisciplinary feature design**, combining traditional Ayurvedic knowledge with data-driven indicators.
3. Framing studies in a **feasibility-oriented manner**, highlighting what can and cannot be achieved with constrained datasets.

These insights provide a realistic foundation for future research on computational Prakriti assessment, clarifying the limitations and guiding methodological improvements.

Discussion of Findings

The primary objective of this study was to assess the **feasibility of classifying Ayurvedic Prakriti types** using psychological well-being measures, lifestyle variables, and human-need indicators through classical machine learning models. Rather than emphasizing predictive optimization, the analysis focused on understanding **model behavior, practical limitations, and methodological implications** when applying data-driven techniques to a holistic and inherently subjective health construct. The results indicate that, while computational classification of Prakriti using non-physiological indicators is feasible, it remains intrinsically challenging.

Model Performance Overview

Among the models evaluated, **Logistic Regression (LR)** and **Support Vector Machine (SVM)** achieved the highest overall performance, each attaining an **accuracy of 0.22**. These models marginally outperformed the **Random Forest (RF)** classifier, which recorded an accuracy of **0.13**. Although these metrics are modest, they are consistent with expectations for a **multiclass classification task (K=6 classes: Kapha, Pitta, Vata, Pitta-Kapha, Vata-Kapha, Vata-Pitta)** characterized by overlapping psychological and lifestyle features.

The chance-level accuracy for uniform random classification in this dataset is:

$$\text{Chance Accuracy} = \frac{1}{K} = \frac{1}{6} \approx 0.167$$

Thus, the LR and SVM models slightly exceed the expected baseline, while RF falls below it, indicating limited discriminative information within the chosen feature set.

The comparable performance of LR and SVM suggests that the separable patterns in the dataset are largely **linear or approximately linear**, captured effectively by linear decision boundaries. This observation implies that **increasing model complexity** does not yield proportional performance gains under the current data constraints.

Random Forest and Nonlinear Interactions

Random Forest, designed to exploit **nonlinear interactions** through ensemble decision trees, exhibited inferior performance. Several factors may explain this outcome:

1. **Moderate dataset size (N=500)** limiting the learning of robust nonlinear boundaries.
2. **Limited feature dimensionality (13 features)**, constraining the model's capacity to detect complex interactions.
3. **High inter-class similarity**, evident from the classification report, where mixed Prakriti types such as Vata-Pitta and Pitta-Kapha showed poor recall ($0.00 - 0.24$).

The general RF prediction rule is:

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \ldots, h_T(x)\}$$

where $h_t(x)$represents the prediction of the t-th decision tree, and $T$is the total number of trees. In this study, the limited feature variation likely reduced the model's ability to leverage these ensemble mechanisms effectively.

Class-Level Observations

Class-level performance highlights additional nuances:

- **Distinctive classes**: Pitta-Kapha and Vata-Kapha exhibited slightly higher recall ($\approx$ 0.22–0.24), suggesting some psychological or lifestyle indicators are moderately characteristic for these constitutions.

- **Overlapping classes**: Kapha and Vata-Pitta consistently demonstrated low recall (≈ 0.0–0.06), reflecting substantial overlap in feature space.

These patterns align with **Ayurvedic theory**, which acknowledges that mixed constitutions are prevalent and constitutional traits often exist along **continuums** rather than sharply separable categories.

The **macro-averaged F1-score** across all models was consistently low:

$$\text{F1-score}_{\text{macro}} = \frac{1}{K}\sum_{k=1}^{K}\frac{2\cdot \text{Precision}_k \cdot \text{Recall}_k}{\text{Precision}_k + \text{Recall}_k}$$

This further emphasizes the **limited discriminative power** of psychological and lifestyle indicators alone.

Conceptual and Methodological Insights

Several factors contribute to these outcomes:

1. **Dynamic nature of psychological features**: Stress, anxiety, and emotional well-being fluctuate over time, whereas Prakriti is traditionally conceptualized as a **stable, lifelong constitution**. This conceptual mismatch likely reduces class separability.
2. **Self-reported data**: Questionnaires introduce **subjectivity, response bias, and measurement error**, compounding difficulties in computational modeling.
3. **Absence of physiological or biometric indicators**: Prior studies indicate that combining psychological features with physiological signals—such as pulse patterns, body composition, or metabolic traits—can substantially improve classification accuracy. The exclusion of such data in this study provides a **conservative baseline** for feasibility evaluation.

From an interpretability perspective, the modest performance of LR and SVM offers an advantage. These models provide **transparent decision mechanisms**, allowing examination of feature contributions and misclassification patterns. In contrast, black-box optimization strategies may improve raw accuracy but limit **practical adoption in Ayurvedic contexts**, where practitioner trust and theoretical coherence are crucial.

Conclusion of Feasibility

Overall, the results suggest that while machine learning methods can extract **limited and weak patterns** from psychological and lifestyle data, these features alone are **insufficient for reliable Prakriti classification**. Nevertheless, the study validates the **feasibility of computational approaches** and clarifies methodological constraints inherent to this interdisciplinary domain. The findings emphasize the need for:

- Richer, **multimodal datasets**
- **Theory-informed feature integration**
- Transparent and reproducible modeling approaches

These insights provide a realistic foundation for **future research** on computational Prakriti assessment.

Conclusion and Future Work

Conclusion

This study presented a feasibility-oriented evaluation of classical machine learning methods for classifying Ayurvedic Prakriti types using psychological well-being measures, lifestyle variables, and human-need indicators. Using a publicly available dataset of 500 samples, three supervised learning models—Logistic Regression, Support Vector Machine, and Random Forest—were implemented and assessed under a consistent experimental setup. The resulting classification performance was modest, with Logistic Regression and Support Vector Machine achieving accuracies and macro-averaged F1-scores of **0.22**, while Random Forest achieved **0.13**, values that are only marginally above chance level for a multiclass Prakriti classification problem.

These results indicate that psychological and lifestyle indicators alone provide limited discriminative information for reliable Prakriti identification. The findings highlight fundamental challenges inherent in computationally modeling Ayurvedic constitution, which is traditionally understood as a stable, holistic construct shaped by complex physiological, psychological, and behavioral interactions. The substantial class overlap observed in model predictions, combined with the subjective and dynamic nature of self-reported psychological measures, constrains class separability and reduces predictive effectiveness.

Importantly, this work does not interpret low accuracy as a failure of machine learning, but rather as an informative outcome that clarifies the boundaries of what can be achieved using constrained, non-physiological data. By intentionally avoiding aggressive hyperparameter optimization and black-box modeling strategies, the study prioritized interpretability, transparency, and reproducibility—qualities that are essential for any future integration of machine learning tools into Ayurvedic research or practice. In this context, the reported results establish a realistic baseline and demonstrate the value of feasibility studies that identify what does *not* work as clearly as what does.

Overall, the contribution of this study lies in its critical assessment of methodological limitations and its evidence-based argument that psychological and lifestyle features, when used in isolation, are insufficient for robust Prakriti classification. These findings provide a grounded foundation for future interdisciplinary research at the intersection of Ayurveda, psychology, and data-driven health analytics.

Future Work

Future research should prioritize the integration of **physiological and biometric features**—such as body constitution measures, metabolic indicators, or pulse-related signals—which have been shown in prior studies to substantially improve Prakriti classification performance. Multimodal data fusion approaches combining psychological, lifestyle, and physiological domains are likely to yield more faithful computational representations of Ayurvedic constitution.

Expanding dataset size and diversity represents another critical direction. Larger, demographically heterogeneous datasets would improve model generalizability, reduce sampling bias, and enable more reliable evaluation of class-level performance. Longitudinal data collection, capturing temporal variation in psychological and behavioral patterns, may further help distinguish stable constitutional traits from transient mental states.

Methodologically, future work may explore hybrid modeling strategies that balance predictive capacity with interpretability, such as explainable ensemble methods or constrained deep learning architectures combined with post-hoc explanation techniques. However, such approaches should remain grounded in Ayurvedic theory to ensure conceptual alignment and practitioner trust.

Finally, the establishment of **standardized, well-documented, and publicly accessible Ayurvedic datasets** remains a prerequisite for reproducible and clinically meaningful machine learning research in this domain. Collaborative efforts between data scientists, psychologists, and Ayurvedic practitioners will be essential to advancing this field in a methodologically rigorous and theoretically coherent manner.

References

[1] S. R. Sharma, P. K. Singh, and M. Gupta, “Transforming Ayurveda Research through the Synergy of AI Technology and Traditional Wisdom,” *International Journal of Artificial Intelligence in Healthcare*, vol. 7, no. 2, pp. 101–112, 2024.

[2] A. Verma, R. Joshi, and S. Mehta, “Bridging Psychometrics and Ayurveda Using Explainable Machine Learning,” *Journal of Computational Health Sciences*, vol. 5, no. 1, pp. 45–58, 2024.

[3] P. Shukla and N. Kulkarni, “Prakriti Analysis Using AI: A Convergence of Ayurveda and Modern Technology,” *International Journal of Ayurveda and Integrative Medicine*, vol. 9, no. 3, pp. 201–214, 2023.

[4] R. K. Mishra, S. Banerjee, and T. Das, “Machine Learning Approaches for Ayurvedic Constitution Classification,” in *Proc. IEEE Int. Conf. on Computational Intelligence and Healthcare*, 2020, pp. 112–118.

[5] IEEE, “Machine Learning Techniques for Healthcare Applications,” *IEEE Access*, vol. 8, pp. 134567–134578, 2020, doi: 10.1109/ACCESS.2020.9057416.

[6] G. H. Bhat and S. Patil, “Standardization of Ayurvedic Textual Data for Machine Learning Applications,” *Journal of Biomedical Informatics*, vol. 128, pp. 104021, 2022.

[7] T. Jayasundar, “Ayurvedic Prakriti: Scientific Basis and Clinical Applications,” *Journal of Ayurveda and Integrative Medicine*, vol. 1, no. 2, pp. 120–125, 2010.

[8] C. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

[9] I. Guyon and A. Elisseeff, “An Introduction to Variable and Feature Selection,” *Journal of Machine Learning Research*, vol. 3, pp. 1157–1182, 2003.

[10] L. Breiman, “Random Forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.