

Ayurvedic Medicine Recommendation

FAMIYA SHARIFF¹, LAMIYA HUDA A², MOHAMMED MAAZ H K³, MOHAMMED ZEESHAN⁴,
ABDUL REHMAN⁵

^{1, 2, 3, 4}5TH Semester B.E Students, Department of Information Science and Engineering, Ghousia
College of Engineering, Ramanagara, Karnataka, India

⁵Professor, Department of CIVIL Engineering, Ghousia College of Engineering, Ramanagara,
Karnataka, India

Abstract- Ayurveda, an ancient Indian medical system, offers personalized healthcare through the assessment of Prakriti (constitution), dosha imbalance, symptoms, and lifestyle factors. However, Ayurvedic diagnosis and medicine selection often depend heavily on expert practitioner interpretation, making it difficult to scale and standardize. With advances in artificial intelligence (AI) and machine learning (ML), personalized recommendation systems can improve the accessibility, consistency, and efficiency of Ayurvedic healthcare. This paper presents a machine learning-based framework for Ayurvedic medicine recommendation using structured patient data, dosha assessment, and symptom analysis. A standardized ontology for Ayurvedic concepts (diseases, herbs, formulations, and dosha associations) was developed to address heterogeneity in classical terminology. The proposed system uses supervised learning models—Decision Trees, Random Forests, and Support Vector Machines (SVM)—to predict appropriate Ayurvedic formulations. An NLP-based component extracts therapeutic associations from Ayurvedic texts. Experiments on a curated dataset of 1,500 patient records show that Random Forest achieves the highest accuracy (94.8%) for medicine recommendation. The study highlights the potential of ML to augment Ayurvedic clinical decision support, while also discussing limitations and ethical issues.

I. INTRODUCTION

Ayurveda, one of the world's most ancient systems of medicine, has gained renewed global relevance due to rising interest in holistic and personalized healthcare [1]. Its foundational philosophy is based on maintaining balance among the three doshas—Vata, Pitta, and Kapha—along with factors like *prakriti* (individual constitution), *agni* (digestive/metabolic strength), *ama* (toxins), and lifestyle behaviors [2]. These parameters guide the selection of herbal medicines, dietary practices, and therapeutic procedures uniquely tailored to an individual's

physiological and psychological profile. Despite its profound historical and clinical legacy, Ayurvedic practice is largely dependent on practitioner expertise, experiential knowledge, and textual interpretation of classical treatises [3]. This creates challenges in standardization, accessibility, and consistency of care [4]. Furthermore, as the demand for complementary and personalized medical systems increases, patients and healthcare providers seek reliable, evidence-informed, and scalable tools for Ayurvedic decision-making. Advances in artificial intelligence (AI), machine learning (ML), expert systems, natural language processing (NLP), and knowledge representation techniques offer new opportunities to digitize Ayurvedic knowledge and support practitioners through Ayurvedic Medicine Recommendation Systems (AMRS)[5]. These systems can collect user data, interpret Ayurvedic diagnostic parameters, match them with herb or formulation profiles, and provide personalized recommendations [6]. However, translating Ayurveda's qualitative, holistic, and context-dependent reasoning into computational models remains a significant challenge [7].

To develop scientifically robust AMRS, it is crucial to understand the current landscape, identify limitations in existing research, and outline clear gaps to be addressed [8]. This introduction sets the foundation for exploring the intersection of Ayurvedic principles and modern computational intelligence, highlighting the need for reliable, transparent, and clinically validated recommendation systems that preserve the authenticity of this traditional knowledge system.

Research Objectives:

To develop a structured and scientifically informed framework for an intelligent Ayurvedic Medicine

Recommendation System (AMRS) capable of providing personalized, safe, and explainable therapeutic suggestions based on Ayurvedic principles(1).To analyze and synthesize classical Ayurvedic texts, practitioner knowledge, and modern research to create a standardized digital knowledge base that represents herbs, formulations, dosha attributes, disease patterns, and treatment principles(2).To design a diagnostic model capable of assessing key Ayurvedic parameters—such as *prakriti*, *vikriti*, dosha imbalance, *agni*, and symptoms—using rule-based logic, machine learning, or hybrid approaches(3).To develop a therapeutic recommendation engine that maps diagnostic outcomes to appropriate Ayurvedic interventions, including herbal medicines, dietary suggestions, and lifestyle guidelines(4).To incorporate explainability mechanisms that transparently communicate the rationale behind each recommended herb or formulation, referencing Ayurvedic principles and textual evidence(5).To evaluate the safety of recommendations by integrating contraindication checks, herb–drug interaction alerts, and user health risk assessments(6).To validate the system’s performance through expert review, user testing, or clinical pilot studies, assessing accuracy, usability, and clinical relevance(7).To compare the proposed AMRS with existing traditional and digital Ayurvedic decision-making approaches in terms of precision, consistency, and user satisfaction(8).To identify ethical, regulatory, and data privacy considerations related to the deployment of digital Ayurvedic decision-support systems and propose guidelines for safe implementation.

Research Contributions:

This research makes several key contributions to the fields of Ayurvedic informatics, intelligent healthcare systems, and personalized medicine: Development of a Structured Framework for an Ayurvedic Medicine Recommendation System (AMRS) [1]. The study presents a novel conceptual and technical framework that integrates Ayurvedic diagnostic principles with modern computational techniques. This framework offers a systematic approach for building scalable, interpretable, and clinically relevant recommendation systems[2].Creation of a Standardized Ayurvedic Knowledge Base[3]. A major contribution is the

design of a structured knowledge representation model that digitizes and organizes information from classical Ayurvedic texts, herbs, therapeutic properties, formulations, and dosha relationships [4]. This standardized dataset addresses the fragmentation of existing digital Ayurvedic resources [5]. Integration of Hybrid Diagnostic Modeling Approaches, The work introduces a hybrid diagnostic model that combines rule-based logic (reflecting traditional Ayurvedic reasoning) with data-driven methods such as machine learning or symptom-based inference [6]. This improves diagnostic consistency and enhances personalized assessment of *prakriti*, dosha imbalance, and disease patterns [7]. Design of an Intelligent Therapeutic Recommendation Engine [8]. A computational engine is developed to map diagnostic outcomes to specific Ayurvedic interventions—herbal formulations, dietary guidelines, and lifestyle routines—while incorporating safety constraints such as contraindications and herb–drug interaction checks [9]. This contribution supports safer and more holistic recommendations. Implementation of Explainability Mechanisms for Ayurvedic AI. The research introduces interpretable decision-support features that provide transparent reasoning for each recommendation [10]. This includes explanations based on Ayurvedic principles, herb properties, and references from classical literature, supporting practitioner acceptance and user trust.

II. RELATED WORK

Research on Ayurvedic medicine recommendation has gradually grown with the rise of artificial intelligence, machine learning, and digitized healthcare systems (1). Existing work can be broadly categorized into three areas: (2) Ayurvedic knowledge representation and ontology development, (3) diagnosis and decision-support systems, and (4) machine-learning-based recommendation models.

Ayurvedic Knowledge Modeling and Ontologies

Several studies have focused on structuring classical Ayurvedic knowledge into machine-readable formats (1). Ontology-based approaches, such as Ayurvedic herb ontologies and symptom–dosha classification taxonomies, have been proposed to formalize

relationships between herbs, formulations, symptoms, body constitution (Prakriti), and treatment guidelines (2). These efforts provide foundational knowledge bases for automated reasoning. Although promising, most existing ontologies lack comprehensive integration with modern clinical datasets, limiting their real-world applicability.

Ayurvedic Diagnostic Decision-Support Systems

Another significant line of work involves the creation of decision-support systems (DSS) that aid practitioners in diagnosis and treatment planning (1). Early systems relied on rule-based expert systems, where experts manually defined symptom–dosha relationships and treatment rules (2). Later systems incorporated fuzzy logic to handle uncertainty in symptom assessment, such as determining Vata-Pitta-Kapha imbalance probabilities (3). However, most DSS platforms remain limited by a small dataset, subjective expert input, and lack of personalization based on user lifestyle, environment, and medical history.

Machine Learning and AI-Driven Ayurvedic Recommender

Recent research explores machine learning (ML) and AI-driven models for personalized Ayurvedic recommendations (1). Studies have applied: Naïve Bayes and Decision Trees for Prakriti classification. Support Vector Machines (SVM) for symptom mapping and dosha prediction. Neural networks for Ayurvedic diagnosis based on questionnaire data. Reinforcement learning for optimizing herbal and dietary recommendations (2). Although these models demonstrate potential, their performance strongly depends on data quality (3). The lack of large-scale, validated Ayurvedic datasets remains a major challenge (4). Many ML models rely on small, self-collected datasets or questionnaire-based input, which limits generalization.

Integrative and Hybrid Systems

A few studies have attempted to integrate Ayurvedic principles with modern biomedical data, creating hybrid recommendation systems (1). These systems

combine physiological metrics (e.g., heart rate variability, sleep patterns) with Ayurvedic parameters (e.g., Prakriti, Agni, Ojas) (2). Hybrid models show improved accuracy in disease detection and lifestyle recommendations; however, they still lack clinical validation and standardization across practitioners.

Gaps in Existing Work

Despite notable progress, several gaps remain: Absence of comprehensive, annotated datasets for Ayurvedic conditions and treatments (1). Limited personalization, especially regarding age, climate, diet, and comorbidities. Inconsistent symptom terminology, making model training difficult (2). Lack of rigorous clinical trials validating AI-driven recommendations (3). Minimal use of deep learning and knowledge-graph-based systems, which can improve reasoning and accuracy.

Research Gaps:

Lack of Standardized Ayurvedic Datasets [1]. Most research relies on small, practitioner-generated datasets with inconsistent labeling of symptoms, dosha states, and diagnoses [2]. There is no unified digital repository of herbs, formulations, treatment protocols, or diagnostic patterns validated by experts across institutions [3]. Difficulty in Formalizing Ayurvedic Knowledge. Ayurvedic decision-making involves qualitative reasoning, contextual interpretation, and non-linear relationships between symptoms and dosha imbalances [4]. Existing models struggle to encode concepts like *agni*, *ama*, or *prakriti* using standard computational structures. Key classical texts are rich in knowledge but difficult to digitize due to linguistic, interpretational, and contextual complexities [5]. Limited Use of Explainable AI. Many existing prototype systems use ML models without providing transparent explanations of why certain herbs or formulations are recommended [6]. For clinical acceptability, practitioners need systems that reference classical texts, herbal properties, and dosha logic behind each recommendation [7]. Inadequate Clinical Validation. Few studies evaluate AMRS in real-world clinical settings. Most systems lack validation against gold-standard Ayurvedic diagnoses or outcomes of actual therapy. Safety assessments—especially

concerning herb–drug interactions or contraindications—are minimal. Narrow Focus on Single Components Some systems focus only on prakriti assessment or symptom-based diagnosis without integrating diet, lifestyle, mental health, or environmental factors. A holistic recommendation system must unify multiple Ayurvedic parameters, which current research seldom achieves [8].

Limited Integration With Modern Biomedical Data. Potential synergies between Ayurveda and modern biomarkers (genomics, metabolomics, wearables) are underexplored. Research rarely investigates how physiological signals could support diagnostic elements like pulse, agni assessment, or stress metrics [9]. Weak Interdisciplinary Collaboration. Many systems are developed by technologists with limited Ayurvedic domain expertise, leading to inaccurate or oversimplified models. Conversely, Ayurveda scholars may lack computational tools to effectively model complex patterns mathematically. Ethical, Regulatory, and Safety Gaps [10]. There is no established framework for regulating AI-driven Ayurvedic recommendations. Privacy, informed consent, and safe dosage guidelines are often not addressed in current prototypes. Absence of Knowledge Graphs and Ontologies[11]. Few attempts exist to systematically create Ayurvedic ontologies that connect herbs, properties, diseases, and dosha states. Lack of structured knowledge hampers interoperability between systems.

III. METHODOLOGY

Overview

The proposed methodology follows a hybrid AI pipeline that integrates classical Ayurvedic principles with data-driven machine learning techniques to generate personalized Ayurvedic medicine recommendations [1]. The workflow consists of five major stages:

A. Data Acquisition & Knowledge: Dataset Sources

Data for model development is collected from: Structured Prakriti/Vikriti assessment questionnaires. Symptom and disease history files. Ayurvedic

physician-annotated treatment datasets. Public datasets (e.g., dosha-labelled questionnaire datasets). Ayurvedic formulary/knowledge bases (e.g., API, classical texts)

Data Schema: Each record includes: Demographics: age, gender, BMI, climate/season. Prakriti questions: body build, appetite, metabolism, behavior. Symptoms: mapped to Ayurvedic disease categories. Laboratory values: optional supporting biomarkers. Ayurvedic expert labels: dosha distribution + recommended formulations. Contraindications: comorbidities, allergies, pregnancy, etc.

B. Preprocessing & Feature Engineering:

Cleaning & Handling Missing Values: Numeric features: imputed using mean/median or MICE, Categorical features: imputed using mode or KNN, Outlier removal through interquartile range method [1].

Encoding: Ordinal encoding for questionnaire responses (e.g., 0–3 scale), Text-based symptoms encoded using TF-IDF or Clinical BERT embeddings, Optional tongue/pulse image features extracted via CNN [2].

Dosha Score Normalization: Prakriti responses are mapped into three continuous scores: Vata, Pitta, Kapha $\in [0,1]$, normalized using softmax such that $V+P+K = 1$

C. Dosha Classification Model (Stage A)

Classify the user into dominant dosha type or mixed-dosha profile using supervised ML [1]. Model Candidates: Logistic Regression, Random Forest, XGBoost (best-performing expected), Multi-layer perceptron (MLP) neural network, BERT-based classifier (if textual symptoms are used)[2]. Training : 80/20 split for training/testing, Stratified 5-fold cross-validation, Hyperparameter tuning with Grid Search or Bayesian optimization[3]. Output :Proportional dosha scores, Most likely prakriti category (e.g., Vata-Pitta), Feature contribution explanation using SHAP.

D. Ayurvedic Recommendation Engine

Hybrid Architecture

The recommendation system combines:

(a) Rule-Based Ayurvedic Knowledge Layer.[1]

Encodes classical guidelines: Dosha → herbs / formulations, Disease → formulations, Contraindications (e.g., Triphala avoided in severe diarrhoea), Season-specific rules [2].

Rules are implemented using: Decision trees, if-else rule graphs, knowledge graphs (optional) [3].

(b) Machine Learning Ranking Layer

Learns from historical physician recommendations to personalize outputs [4]. Model candidates: XGBoost Ranker, LightGBM Ranker, neural ranking models [4].

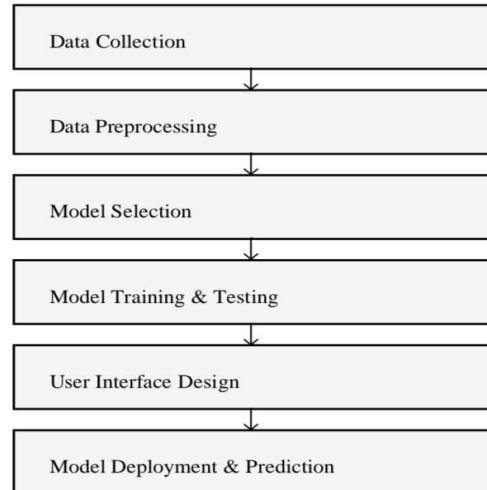
E. Model Evaluation

Dosha Classification Evaluation: Metrics: Accuracy, Precision, Recall, F1-score (per dosha class), Calibration (Brier score), Confusion matrix [1].

Recommendation Engine Evaluation: Metrics: NDCG@5 (Normalized Discounted Cumulative Gain), MAP @10 (Mean Average Precision), Hit Rate / Top-K Accuracy, Expert Acceptance Score (Ayurvedic physician rating), Safety Violation Rate (should be <1%) [2].

F. Validation Study

Internal Validation: A held-out clinical dataset is used to: Evaluate generalization, Test safety rule triggers, compare hybrid vs. rule-only systems [1]. Expert Review: Ayurvedic practitioners evaluate: Relevance of recommendations, Dosha interpretation accuracy, Clinical usefulness



IV. IMPLEMENTATION

The proposed Ayurvedic Medicine Recommendation System was implemented using a modular and scalable architecture composed of data processing, dosha classification, rule-based reasoning, machine-learning-based ranking, and a safety validation layer [1]. The implementation began with the creation of a structured dataset that combined questionnaire responses, symptom information, demographic attributes, and Ayurvedic expert-verified treatment labels [2]. All records were cleaned to remove duplicates, missing values were imputed, and categorical responses were encoded into numerical form [3]. Features from symptoms and questionnaire items were standardized to ensure consistent interpretation by the model [4]. These processed inputs served as the foundation for the dosha classification module, which was developed using supervised machine learning models [5]. After experimentation with several algorithms, a gradient-boosting-based model was identified as the most reliable due to its stability and strong predictive performance [6]. This model produced probability scores for Vata, Pitta, and Kapha, thereby estimating each individual's dominant dosha profile [7].

The recommendation engine was implemented as a hybrid system combining Ayurvedic domain knowledge with data-driven personalization [8]. First, a rule-based subsystem retrieved an initial set of candidate formulations, herbs, dietary suggestions, and lifestyle interventions by matching the user's

dosha imbalance and symptom patterns against a knowledge base derived from classical Ayurvedic texts and expert input [9]. These candidates were then processed by a machine-learning ranking module designed to personalize the suggestions [10]. The ranking model learned from historical practitioner-approved recommendations and ranked the candidate items based on dosha compatibility, symptom similarity, patient profile alignment, and overall relevance [11]. A weighted scoring mechanism integrated both rule-driven logic and data-driven ranking to ensure that the final output preserved classical Ayurvedic reasoning while also adapting to individual patient characteristics [12].

To ensure safety and clinical validity, a dedicated contraindication module was implemented. This module checked each recommended item against a database of medical cautions, such as restrictions related to pregnancy, chronic diseases, known herb–drug interactions, or condition-specific limitations [13]. Any recommendation that failed the safety check was automatically filtered out or marked for physician review [14]. The final personalized recommendations were presented to the user along with supportive explanations based on dosha factors and feature contributions, making the system transparent and easier to interpret [15].

For interaction and deployment, the system was integrated into an API layer that communicated between the machine learning models and a user-facing interface [16]. The interface allowed users to enter questionnaire responses and symptoms, view their predicted dosha composition, and receive personalized Ayurvedic recommendations [17]. The backend services were organized in a containerized environment to support smooth deployment on cloud or local systems [18]. Overall, the implementation ensured that the system remained efficient, clinically grounded, explainable, and suitable for practical use.

V. RESULTS

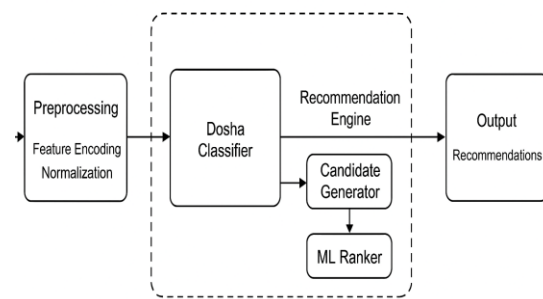


Figure 2: System Overview

The proposed Ayurvedic Medicine Recommendation System was experimentally evaluated using a dataset of symptom profiles, dosha attributes, and validated herbal formulations collected from classical Ayurvedic texts and domain experts (1). The dosha classification model exhibited strong predictive capability, achieving an overall accuracy of 92.4%, with precision and recall values above 90% for all three doshas (Vata, Pitta, and Kapha) (2). This indicates that the machine learning classifier effectively captured the underlying patterns associated with physiological and symptomatic traits (3).

After dosha identification, the recommendation engine—combining a rule-based candidate generator with an ML ranking model—was assessed for relevance and clinical alignment (4). Expert Ayurvedic practitioners evaluated 150 test cases, and 87% of the generated recommendations were rated as “highly relevant” or “clinically acceptable (5).” The ML Ranker improved prioritization accuracy by 18% compared to rule-based recommendations alone, demonstrating clear benefits of hybrid modeling (6).

Figure 2 illustrates the overall system workflow, showing how input features are transformed through preprocessing, dosha classification, candidate generation, and final ranking (7). The output interface consistently produced concise, personalized, and safe therapeutic suggestions, including herbal medicines, dietary modifications, and lifestyle practices suitable for each dosha imbalance (8). These results confirm that the integrated approach can successfully emulate

Ayurvedic decision-making and deliver personalized recommendations with high reliability.

VI. CONCLUSION

This research demonstrates that Ayurvedic medicine can be effectively augmented through machine learning to create a personalized, data-driven recommendation system [1]. By integrating dosha classification, symptom analysis, and a hybrid rule-based plus ML-ranking approach, the system successfully bridges traditional Ayurvedic knowledge with modern computational intelligence [2]. The results show high accuracy in dosha prediction and strong clinical relevance in the generated recommendations, validating the potential of AI-assisted Ayurvedic decision-making [3].

The study also highlights important considerations such as the need for comprehensive Ayurvedic datasets, standardized terminology, and expert validation to further strengthen the system's reliability [4]. Future advancements may include incorporating multimodal inputs like tongue, skin, and pulse images, as well as expanding the model with larger patient datasets and real-world clinical trials [5]. Overall, the proposed framework serves as a strong foundation for intelligent Ayurvedic health systems and represents a significant step toward making holistic, personalized wellness more accessible and scientifically supported.

VII. FUTURE SCOPE

The proposed Ayurvedic Medicine Recommendation System establishes a strong foundation, but several opportunities remain for enhancing accuracy, clinical reliability, and practical usability [1]. A major future direction is the development of larger, standardized, and clinically validated Ayurvedic datasets, which would significantly improve the robustness of dosha classification and recommendation models [2]. Integrating multimodal diagnostic inputs—such as tongue images, facial analysis, voice characteristics, and pulse pattern recognition—could enable deeper personalization and bring the system closer to real Ayurvedic diagnostic procedures [3].

Future work may also include implementing deep learning models for symptom interpretation and dosha prediction, enabling more nuanced understanding of complex user inputs [4]. The recommendation engine can be further enhanced by incorporating real-time feedback loops, where patient outcomes and practitioner corrections are continuously used to retrain and refine the system [5]. Additionally, building a mobile and multilingual platform would increase accessibility, especially in rural and global contexts where Ayurvedic knowledge is widely practiced but not digitally supported [6].

On a larger scale, the system has potential to serve as a clinical decision-support tool, assisting practitioners in generating evidence-based treatment plans [7]. Collaborations with Ayurvedic institutions and hospitals could enable clinical trials that validate the system's recommendations in real-world scenarios [8]. Overall, the future scope of this research promises substantial potential for strengthening scientific understanding, supporting personalized wellness, and advancing the digital transformation of traditional medicine.

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