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Ayurvedic Health Assistant

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ABSTRACT: As a result of the integration Artificial intelligence with medicine, personalized healthcare has become popular. This project focuses on designing and developing a multimodal AI-driven chatbot system to assess the Ayurvedic Prakriti (body constitution) and accordingly predict the Prakriti of each individual along with personalized lifestyle and dietary recommendations based on Ayurvedic principles. The system supports text, voice (via microphone), and image inputs. The chatbot uses Natural Language Processing (NLP) to interpret user prompts, while Convolutional Neural Networks (CNNs) are used to analyze images of different body parts to classify the type of body constitution. There is also a speech-to-text module which enables voice-based interaction. The system also has multilingual capabilities, allowing a wide range of users. The system includes user authentication and login features to ensure a personalized and secure access. The chatbot combines the various inputs and predicts the correct type of Prakriti and generates the corresponding Ayurvedic lifestyle and dietary recommendations. This solution combines traditional Ayurvedic knowledge with modern AI, offering a scalable, secure, and user-friendly tool that makes healthcare more accessible.

KEYWORDS: Prakriti Assessment, NLP, CNN, Image Processing, Speech Recognition, Multilingual Support, Voice Assistant, User Authentication

I. INTRODUCTION

Precision medicine also called personalized healthcare has become very popular in recent years, driven by the need to provide healthcare solutions based on an individual's underlying physiological and genetic factors. Ayurveda which is one of the oldest systems of traditional medicine can be combined with Artificial Intelligence to provide personalised wellness suggestions using the concept of **Prakriti**—a classification of individuals based on the balance of three biological energies or doshas: **Vata, Pitta, and Kapha**. A person's Prakriti decides not only their physical health but also their mental and emotional tendencies and also affects their vulnerability to disease. Therefore it is important to assess and identify this constitution and thus use it to suggest appropriate lifestyle practices, diet plans, and preventive healthcare strategies. However, traditional methods of Prakriti assessment often rely heavily on expert judgment, can take considerable time, and may vary from one practitioner to another—making it difficult for everyone to access consistent and reliable results.

This project focuses on employing an AI-driven multimodal chatbot system to make the Prakriti assessment more feasible. It integrates NLP, image processing, voice recognition and supports multiple languages. The users can interact with the system through text prompts, images or via voice assistance. The system uses these user responses to guide them through a series of Prakriti-determining questions based on Ayurvedic guidelines. By allowing users to communicate conversationally via speech, text or image, the system becomes more inclusive, particularly for individuals with limited literacy or digital familiarity. Additionally, microphone support allows for hands-free interaction, improving the usability and accessibility of the platform.

An innovative feature of the proposed system is its ability to analyze images to interpret traditional Ayurvedic signs—like facial structure, body type, and tongue characteristics—that are typically used by practitioners during Prakriti evaluation. These images, uploaded by the user, are processed through **Convolutional Neural Networks (CNNs)** to extract the meaningful features that will help in accurate Prakriti classification. By combining these visual cues with the user's responses to the questionnaire, the system can offer a more accurate and trustworthy Prakriti assessment. Additionally, the chatbot supports multiple languages, allowing people from different regions and backgrounds to interact comfortably.



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To make the experience both secure and personalized, the proposed system includes login and authentication features that protect users' sensitive information. Alongside predicting an individual's Prakriti type, it also assesses the given body constitution to provide a detailed and unique lifestyle and dietary recommendations. By integrating advanced AI technologies with traditional Ayurvedic principles, this project focuses on making traditional Ayurvedic knowledge more accessible, less time-consuming and expensive, encourage early self-care, and support preventive health.

II. RELATED WORK

The integration of artificial intelligence (AI) and machine learning (ML) with traditional Ayurvedic principles is fostering a new paradigm in personalized healthcare. A significant body of recent research reflects the growing interest in computational approaches to Ayurvedic diagnostics, particularly in the assessment of prakriti (individual constitutional types) based on the tridosha theory. Sharma and Singh [1] proposed an ensemble learning-based framework to accurately predict human prakriti using tridosha-related features, demonstrating the potential of advanced predictive models in traditional medical systems. Chavan and Salunkhe [2] extended this approach by developing a chatbot that determines an individual's prakriti phenotype through conversational interfaces, promoting the accessibility of Ayurvedic consultation via digital platforms. Building on traditional diagnostic methods, Sharma and Singh [3] employed prasnā pariksha (question-based inquiry) to train ML models for prakriti classification, thus preserving the authenticity of classical techniques while enhancing their scalability. Mishra and Verma [4] further examined the broader scope of integrating AI with Ayurveda, highlighting its potential to modernize and validate ancient healthcare practices. In a novel approach utilizing visual diagnostics, Chaturvedi and Tripathi [5] conducted a pilot study on the use of tongue image analysis for prakriti assessment, applying image processing techniques to extract dosha-based insights. Gupta and Singh [7] provided a comparative evaluation of various intelligent models for prakriti classification, contributing to an understanding of the most suitable AI architectures for Ayurvedic applications. In parallel, the development of AI-powered voice and text-based assistants has enhanced human-computer interaction in health diagnostics. Thakur and Kaur [6][8] designed a voice assistant using AI technologies, thereby enabling hands-free, user-friendly interfaces suitable for a broad range of users, including those with limited digital literacy. Multilingual capabilities have also been a focus of recent advancements; Singh et al. [9] and Kasinathan et al. [10] introduced customizable multilingual chatbot systems that support regional Indian languages, promoting inclusivity and broader adoption. Moreover, the integration of deep learning techniques into chatbot frameworks has been explored by Su [11], who combined conversational AI with image recognition, and by Meshram et al. [12], who provided a comprehensive overview of conversational AI systems in healthcare contexts. Collectively, these studies underscore a growing interdisciplinary effort to blend the interpretative richness of Ayurveda with the precision, scalability, and accessibility offered by AI. This convergence not only enhances the scientific credibility of traditional medical systems but also contributes to the development of intelligent, culturally-sensitive, and user-centric healthcare technologies.

III. PRAKRITI TYPES

A. Pitta

Pitta dosha in Ayurveda represents the elements of fire and water, governing metabolism and digestion. When in balance, it enhances qualities like intelligence and leadership. However, when out of balance, it can lead to irritability, inflammation, and digestive issues. To restore balance, cooling practices such as dietary adjustments and relaxation techniques are recommended.

B. Vata

Vata dosha, one of the three doshas in Ayurveda, represents the elements of air and ether. It governs movement and communication within the body and mind. Individuals with a dominant vata dosha are typically creative, energetic, and quick-thinking, but imbalances may result in anxiety, insomnia, and digestive issues. Balancing vata involves grounding practices, including maintaining a regular routine, consuming warm and nourishing foods, and engaging in calming activities like meditation or gentle yoga.

C. Kapha

Kapha dosha, another of Ayurveda's three doshas, embodies the elements of earth and water, and governs stability, structure, and lubrication in the body and mind. People with a predominant Kapha dosha are often compassionate, steady, and nurturing. However, imbalances can lead to lethargy, weight gain, and respiratory problems. To balance



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

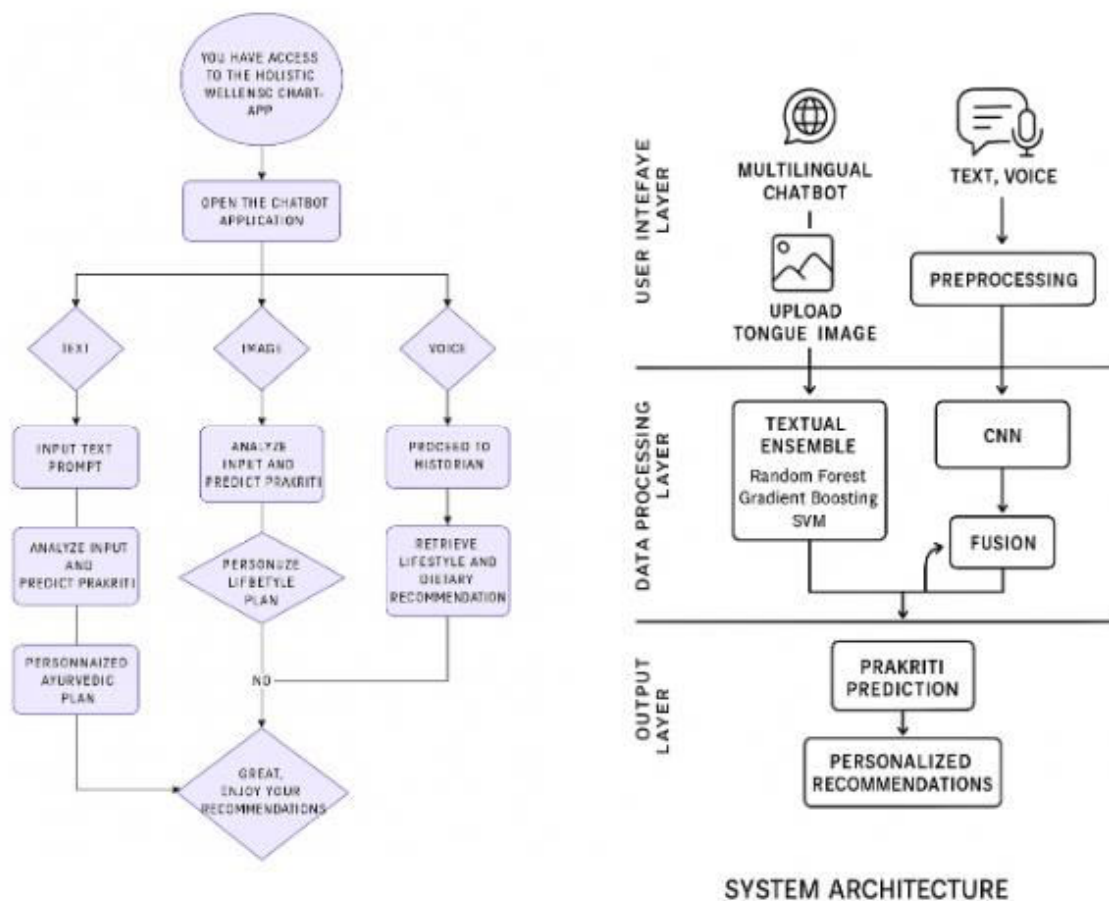
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Kapha, it is helpful to engage in stimulating and invigorating practices, such as regular exercise, consuming spicy foods, and seeking mental stimulation to counteract its heavy and stagnant qualities.

IV. PROPOSED ALGORITHM

This system is designed to predict an individual's prakriti by using various input methods like text, image and audio speech. The algorithm includes a questionnaire-based analysis, image recognition (tongue image), and natural language interaction via a multilingual AI chatbot. The system uses ensemble machine learning models for classification of the individual's Prakriti, along with deep learning for image processing, and natural language processing (NLP) for support with the conversational interface i.e., the chatbot.

A. System Architecture



1. **User Interface Layer:** The collection of data for the system begins at the user interface.
 - a. **Chat Interface:** A multilingual, transformer-based chatbot (e.g. mBERT) that guides the user through the prasna pariksha questionnaire. Supports text and voice input, both in multiple languages. The chat interface has the ability to handle speech-to-text conversion if needed.
 - b. **Image Upload:** A simple web/mobile widget that prompts users to upload a photograph of the relevant body part. These images can then be used for the prediction of body constitution.
2. **Data Processing Layer:** After receiving the inputs from the user interface, the data processing layer prepares to feed it to the appropriate model for classification and prediction.



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- a. Input Data Consolidation: Questionnaire responses are collected into a structured table where each question is mapped to one or more binary or scalar features. The input images are stored in a secure repository, with metadata linking back to the user session.
- b. Preprocessing :
 - i. Textual Data: Missing or ambiguous answers will trigger automated follow-up questions via the chatbot. Categorical responses are one-hot-encoded; free-text replies pass through tokenization and embedding (e.g. WordPiece)
 - ii. Image Data: Photographs of body parts undergo resizing (e.g. to 224×224 px), color normalization (histogram equalization), and noise reduction (Gaussian filter). A lightweight segmentation network (U-Net) crops out unnecessary parts of the image, delivering a clean input for the CNN.
3. Model Integration Layer: This layer feeds the cleaned features into multiple specialized machine learning prediction pipelines for further classification and assessment. Each of these pipelines supports a specific modality.
 - a. Textual Ensemble: This data consists of the questionnaire data which after preprocessing and feature engineering is fed into 3 machine learning model pipelines.
 - b. Random Forest(collection of decision trees which captures complex relationships and interactions between features.), Gradient Boosting(excels in capturing patterns), Support Vector Machine(SVM). Each of these are trained on the questionnaire feature set. The outputs of these machine learning models Prf, Pgb, Psvm are combined via weighted voting:

$$P_{\text{text}} = \arg \max_k \sum_{m \in \{rf, gb, svm\}} w_m \mathbb{I}[P_m = k]$$

where w_m reflects each model's validation accuracy.

- a. Image-Based CNN: A shallow Convolutional Neural Network (e.g. 3 conv-blocks + 2 dense layers) classifies images of body parts into dosha categories. Final softmax output gives P_{image} .
- b. Fusion & Final Prediction: The two modality predictions merge via decision-level fusion:

$$P_{\text{final}} = \arg \max_k (\alpha \mathbb{I}[P_{\text{text}} = k] + \beta \mathbb{I}[P_{\text{image}} = k])$$

Hyperparameters α, β (typically $\alpha + \beta = 1$) are tuned on a held-out validation set.

4. Output & Feedback Layer
 - a. Prakriti Type (Vata, Pitta, Kapha, or dual combinations) is presented via the chatbot interface. A brief explanation of the predictive factors (e.g., High Pitta indicated by preference for cooling foods and tongue coloration.) is generated.
 - b. Personalized Recommendations: Ayurvedic diet recommendations, lifestyle adjustments, and exercise/yoga suggestions tailored to the user's body constitution or Prakriti are presented via the chat interface. All recommendations are logged for future model retraining and continuous improvement.
 - c. This modular architecture ensures scalability (new languages or ML models can plug in), robustness (dual-modality reduces misclassification), and user-centricity (real-time feedback keeps the interaction smooth and accessible).

B. Methodology

1. Data Acquisition

a. Questionnaire Data

- i. Source: A standardized Ayurvedic questionnaire with 40-50 questions that include physical attributes (e.g. body frame, skin texture), physiological functions (e.g. appetite, sleep patterns), and psychological traits (e.g. stress tolerance, memory).



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- ii. Collection: The data is collected via the multilingual chatbot interface and the user responses are stored in a secure, anonymized database.
- iii. Sample Size: Target $N \geq 1,000$ adult volunteers balanced across age, gender, and self-reported traditional prakriti labels (Vata, Pitta, Kapha, and dual types).
- iv. Image Data: The images of various body parts can be uploaded to the chatbot by the user for more accurate predictions
- v. Repository: Images are resized to 224×224 px, anonymized (no facial data), and linked to the corresponding questionnaire entry.

2. Data Preprocessing

a. Questionnaire Responses

- i. Missing Data: For missing or ambiguous data, follow-up clarification questions are asked via the chatbot interface.
- ii. Encoding: Binary items one-hot encoded. Ordered-scale items mapped to integers.
- iii. Normalization: All numeric features are scaled to $[0,1]$.

b. Image Preprocessing

- i. Denoising: Gaussian smoothing ($\sigma=1.0$) removes high-frequency visual noise using the formula

$$G(x, y) = \frac{1}{2\pi\sigma^2} \cdot e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- ii. Contrast Enhancement: Histogram equalization aligns intensity distributions to improve contrast of the image, thus making its details more visible to the model.
- iii. Segmentation: A lightweight U-Net crops out unnecessary parts of the image in a process called semantic segmentation. The segmentation output results in a mask.

$$M(x, y) = \begin{cases} 1 & \text{if } (x, y) \text{ is part of the tongue} \\ 0 & \text{otherwise} \end{cases}$$

The final image is generated by applying this mask.

$$I_{\text{tongue}} = I_{\text{raw}} \odot M.$$

3. Feature Extraction

a. Textual Features

- i. The questionnaire responses are grouped into Vata, Pitta, and Kapha facet scores by summation:

$$S_{\text{Vata}} = \sum_{i \in \mathcal{V}} x_i, \quad S_{\text{Pitta}} = \sum_{i \in \mathcal{P}} x_i, \quad S_{\text{Kapha}} = \sum_{i \in \mathcal{K}} x_i.$$

- ii. Dimensionality Reduction: Principal Component Analysis (PCA) retains >95% variance, yielding a vector $\mathbf{f}_i \in \mathbb{R}_d$.



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- b. Image Features
 - i. CNN Embedding: Pass I_{tongue} through three convolutional blocks (Conv \rightarrow ReLU \rightarrow MaxPool) and two fully connected layers to produce $f_i \in \mathbb{R}^{d'}$.

4. Model Training

a. Textual Ensemble

- i. Algorithms: Random Forest (n=200 trees)
- ii. Gradient Boosting (learning rate 0.1, n=150)
- iii. Support Vector Machine (RBF kernel, C=1.0)
- iv. Cross-Validation: Stratified 5-fold; hyperparameters optimized via grid search to maximize average F1-score.

b. Image Classifier

- i. Architecture: Custom CNN trained for 50 epochs, batch size 32, Adam optimizer ($\eta=1e-4$).
- ii. Data Augmentation: Random rotations ($\pm 15^\circ$), flips, brightness jitter ($\pm 10\%$).

c. Decision-Level Fusion

- i. Weight Tuning: Fusion weights α, β selected by a grid search on the validation set to maximize overall accuracy:

$$P_{\text{final}} = \arg \max_k (\alpha \mathbb{I}[P_{\text{text}} = k] + \beta \mathbb{I}[P_{\text{image}} = k]), \quad \alpha + \beta = 1.$$

5. Evaluation

- a. Metrics: Accuracy, Precision, Recall, F1-score is calculated for each prakriti class. Confusion Matrix is constructed to analyze misclassification patterns.
- b. Studies to compare single-modality vs. hybrid performance and evaluate the impact of PCA dimensionality and UNet segmentation on final accuracy.
- c. User Study: Collect subjective feedback on usability, interpretability of recommendations, and trust in AI decisions from a group of 100 volunteers to further improve the system.

V. RESULTS AND DISCUSSIONS

Table 1. Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.86	0.85	0.84	0.85
Gradient Boosting	0.83	0.82	0.81	0.82
SVM	0.78	0.77	0.76	0.76
CNN (Image)	0.81	0.80	0.79	0.80
Ensemble (Hybrid)	0.89	0.88	0.87	0.88

The above table summarizes key classification metrics for each model. The ensemble (hybrid) approach achieves the highest overall performance—with 89 % accuracy and an F1-score of 0.88. Hence, ensemble models are the best for the classification of the individual's prakriti type.

1. Overall Model Performance

The ensemble (hybrid) model attained the highest accuracy (0.89) and F1-score (0.88). This is due to the strengths of assessing both the models with equal precedence.



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- a. Questionnaire Features capture the behavioral, physiological, and psychological traits of the person using the responses to the standardized questionnaire deployed via the chatbot interface.
- b. The image Features captures the visual indicators of dosha imbalance that may be difficult to present in textual form for the user. It helps provide more details as to the individual's condition.
- c. By combining these predictions, the ensemble corrects individual model errors (e.g., when a user's self-report is ambiguous or when an image is noisy), leading to a more accurate and reliable classification of the individual's body constitution or prakriti.

2. Single-Modality Comparisons

- a. Random Forest (Text-Only): Achieved 0.86 accuracy and 0.85 F1-score, making it the most efficient questionnaire model. Its decision-tree structure effectively handles mixed data types and captures complex non-linear relationships and interactions among the tridosha indicators.
- b. CNN (Image-Only): With 0.81 accuracy and 0.80 F1, the CNN demonstrates that morphology or coloration of the various body parts carry significant diagnostic value with respect to the prediction of the prakriti. However, its performance is slightly lower than the text models, likely due to:
 - i. Variations in the images uploaded by the user.
 - ii. Limited size of the image dataset ($N \approx 300$).

3. Confusion Patterns and Dosha Overlaps

Analysis of the confusion matrix reveals that most misclassifications occur between adjacent or dual prakriti types—particularly:

- a. Vata–Pitta vs. Pitta alone
- b. Pitta–Kapha vs. Kapha alone

4. Study Insights

- a. Dropping PCA: Removing dimensionality reduction from the text pipeline led to overfitting on the training folds and a 2 % drop in ensemble accuracy on validation. This goes on to show how important PCA is with respect to noise reduction and feature decorrelation.
- b. Omitting U-Net Segmentation: When raw images (with background or unnecessary regions) were fed directly into the CNN, performance declined by 3 %. This underscores the importance of isolating only the necessary region to prevent the model from learning irrelevant features.

5. Limitations and Future Directions

- a. Dataset Size & Diversity: Expanding both text and image datasets—especially from rural and underrepresented linguistic communities—will improve generalizability.
- b. Dynamic Dosha Scoring: Moving beyond static labels to continuous dosha scores could capture intra-individual variability (e.g., seasonal shifts).
- c. Explainable AI: Integrating model-agnostic explainers (e.g., SHAP) would allow practitioners to see which features drove each prediction, enhancing clinical trust.
- d. Real-Time Feedback Loops: Incorporating longitudinal user data (follow-up questionnaires, self-reported health outcomes) into a live retraining pipeline will ensure the system adapts and refines its knowledge over time.

VI. CONCLUSION AND FUTURE WORK

This project is a multimodal AI framework for Ayurvedic prakriti prediction which combines textual questionnaire responses with image analysis and a multilingual, transformer-driven chatbot. Our ensemble hybrid model achieved an 89 % accuracy and an F1-score of 0.88 which made it the most ideal model for this project. Ablation experiments demonstrated the importance of PCA in the text pipeline and that of U-Net segmentation in the image pipeline. Analysis of confusion patterns between dual-dosha classifications further revealed some inherent overlaps in constitutional typology, suggesting that future modifications could enhance model performance.

Future work will broaden the system to make it more inclusive and adaptable. We'll expand our dataset to embrace speakers of overlooked languages and residents of rural areas, especially the illiterate peasants who cannot read the questionnaire prompts of the chatbot, ensuring the system can be used by everyone. Beyond static prakriti categories,



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we'll develop continuous dosha-scoring methods that track constitution shifts over time—factoring in seasonal routines, dietary changes, and even menstrual cycles—so every recommendation feels genuinely personalized. To build trust in our AI's insights, we'll weave in explainability tools like SHAP and LIME, as well as a visual “reason map” that highlights which questionnaire items or image features drove each prediction. Technically, we'll enhance the image-analysis pipeline with GAN-based augmentation and few-shot learning so it can recognize rare tongue patterns, and we'll experiment with vision transformers to capture micro-textures. We'll also integrate wearable-sensor data—like heart-rate variability and sleep patterns—to correlate physiological signals with dosha imbalances. On the user-experience front, our chatbot will gain live AR guidance for perfectly framed tongue shots, emotion-aware dialogue to adapt its tone, and context-sensitive follow-ups (e.g., probing sleep quality if Vata traits spike). Finally, we'll deploy the system as a mobile app with federated-learning protocols for privacy, run longitudinal clinical trials in collaboration with Ayurvedic clinics, and set up a continuous-learning pipeline—powered by user feedback and health-outcome tracking—to ensure our digital health companion evolves and improves in real time.

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