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Prakṛti Assessment Through Artificial Intelligence: Classical Foundations, Computational Approaches, And Future Directions In Personalised Āyurvedic Medicine — A Comprehensive Narrative Review

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ABSTRACT

Background- Prakṛti (psychophysiological constitution) is a foundational concept in Āyurveda that determines individual susceptibility to disease, drug response, and therapeutic outcomes. Traditional Prakṛti assessment relies on subjective clinical evaluation — physical examination, questionnaires, and pulse diagnosis — which suffers from inter-practitioner variability, lack of standardisation, and limited scalability. The rapid advancement of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) technologies offers transformative potential for objectifying, standardising, and scaling Prakṛti assessment through computational approaches. Objective- To comprehensively review the classical conceptualisation of Prakṛti in Āyurveda, systematically evaluate contemporary AI and ML approaches for Prakṛti classification including questionnaire-based models, pulse waveform analysis, facial image recognition, tongue diagnosis, genomic data mining, natural language processing, and wearable sensor integration; and to critically assess the current evidence, methodological challenges, ethical considerations, and future directions for AI-driven Prakṛti assessment in personalised medicine. Methods- Classical Āyurvedic texts (Charaka Samhitā Vimāna Sthāna 8, Suśruta Samhitā Śārīra Sthāna 4, Aṣṭāṅgahṛdayam Śārīra Sthāna 3) were reviewed for the Prakṛti framework. Published peer-reviewed literature on AI/ML applications in Prakṛti assessment was searched on PubMed, IEEE Xplore, Scopus, Google Scholar, DHARA, and AYUSH Research Portal using terms 'Prakriti machine learning', 'Ayurveda artificial intelligence', 'constitution classification deep learning', 'pulse diagnosis AI', 'Ayurvedic phenotyping computational', 'Prakriti genomics AI', and related terms. Publications from 2010 to 2025 were included. Grey literature including conference proceedings and dissertations were also considered. Results- Multiple AI/ML modalities have been applied to Prakṛti classification. Questionnaire-based models using Random Forest, SVM, and ANN achieve 75–93% classification accuracy for three-class (Vāta/Pitta/Kapha) discrimination. Pulse waveform analysis using piezoelectric/PPG sensors combined with CNN and LSTM architectures achieves 70–92% accuracy. Facial image analysis using computer vision and transfer learning (VGG16, ResNet) demonstrates 65–85% concordance with expert assessment. Genomic data integration using supervised learning on SNP profiles and gene expression data achieves significant Prakṛti discrimination. NLP-based analysis of classical texts enables automated feature extraction. Wearable IoT platforms combining multi-modal data show promising preliminary results. Key challenges include small datasets, class imbalance, lack of gold-standard labelling, and limited external validation. Conclusion - AI-driven Prakṛti assessment represents a high-potential convergence of traditional knowledge and modern computational science. While current evidence demonstrates feasibility and promising accuracy across multiple modalities, the field requires larger datasets, standardised clinical labelling protocols, multi-modal data fusion approaches, external validation across diverse populations, and robust ethical frameworks for deployment. The integration of AI-based Prakṛti tools into clinical Āyurvedic practice, telemedicine, preventive health screening, and pharmacogenomics could fundamentally transform personalised medicine delivery.

Keywords: *Artificial Intelligence, Āyurveda, Classification, Deep Learning, Machine Learning, Personalised medicine, Phenotyping, Prakṛti, Tridoṣa, Wearable sensors*

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1. INTRODUCTION

Āyurveda, the ancient Indian medical system with roots extending over three millennia, is fundamentally predicated upon the principle of individual biological uniqueness. The concept of *Prakṛti* — the inherent, stable psychophysiological constitution determined at conception — operationalises this principle by providing a systematic framework for classifying individuals into constitutional types based on their dominant Doṣic (bio-energy) profile. Prakṛti influences not only physical morphology and physiological function but also psychological temperament, disease susceptibility, drug metabolism, dietary requirements, and therapeutic responsiveness [1,2].

In many respects, the Prakṛti concept anticipates the core philosophy of modern precision medicine and pharmacogenomics — the recognition that therapeutic efficacy and safety are not uniform across populations but vary systematically with individual biological characteristics. However, while modern precision medicine relies on genomic sequencing, biomarker panels, and computational analysis to individualise treatment, Āyurvedic Prakṛti assessment has historically relied on subjective clinical methods: physical examination, structured interviews, questionnaire instruments, and pulse diagnosis (Nāḍī Parīkṣā) [3,4].

These traditional assessment methods, while clinically rich, face significant limitations in the modern healthcare context: inter-practitioner variability (different Vaidya may classify the same individual differently); lack of standardised, universally adopted assessment tools; time-intensive clinical processes unsuitable for large-scale screening; and inherent subjectivity that hinders reproducibility and scientific validation. These limitations have historically constrained the integration of Prakṛti-based personalisation into mainstream healthcare [4,5].

The rapid advancement of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) technologies in the past decade offers a transformative opportunity to address these limitations. AI-based approaches can potentially objectify Prakṛti assessment, standardise classification, enable scalable population-level screening, fuse multi-modal data sources, and provide reproducible, evidence-based constitutional classification that satisfies both traditional clinical requirements and modern scientific standards. The present review comprehensively examines this emerging convergence of classical Āyurvedic wisdom and computational intelligence.

2. CLASSICAL CONCEPTUALISATION OF PRAKṚTI

2.1 Definition and Determinants

The Charaka Samhitā (Vimāna Sthāna, Adhyāya 8) provides the most comprehensive classical exposition of Prakṛti. The term *Prakṛti* derives from 'pra' (before, primary) + 'kṛti' (creation, making), denoting the 'original nature' — the biological baseline established at conception (*śukra-śoṇita saṁyoge yaḥ doṣaḥ sarvato'dhikaḥ*, i.e., the Doṣa that predominates at the time of union of sperm and ovum determines the Prakṛti) [1]. Once established, Prakṛti remains stable throughout life and serves as the individual's constitutional reference point for health assessment.

Classical determinants of Prakṛti include: *Bīja* (parental genetic material — the dominant Doṣa in Śukra and Ārtava); *Kṣetra* (uterine environment); *Āhāra-Vihāra* of the mother during pregnancy (maternal diet and lifestyle); *Ṛtu* (season at conception and gestation); *Kāla* (time/age factors); and *Mahābhūta Vikāra* (elemental composition of the conceived being). These determinants — genetic, epigenetic, environmental, and temporal — collectively produce the unique Doṣic balance that defines the individual's constitution [1,2,6].

2.2 Classification: Seven Prakṛti Types

Classical texts enumerate seven Prakṛti types based on Doṣic dominance: three mono-Doṣic (Vātaja, Pittaja, Kaphaja), three dual-Doṣic (Vāta-Pittaja, Pitta-Kaphaja, Vāta-Kaphaja), and one balanced (Sama Prakṛti). Each type exhibits a comprehensive set of morphological, physiological, psychological, and behavioural characteristics detailed in the Charaka Samhitā (Vimāna Sthāna, Adhyāya 8) [1].

Prakṛti Type	Physical Features	Physiological Features	Psychological Features	Disease Predisposition
Vātaja	Lean, dry skin, small frame, prominent joints, thin hair	Irregular appetite/digestion, variable energy, light sleep, cold intolerance	Creative, anxious, quick-thinking, enthusiastic, fearful	Neurological, musculoskeletal, constipation, anxiety disorders
Pittaja	Medium frame, warm/oily skin,	Strong appetite, efficient digestion,	Sharp intellect, competitive,	Inflammatory, hepatic, peptic

	premature greying, sharp features	moderate sleep, heat intolerance	irritable, leadership-oriented	disease, hypertension, skin disorders
Kaphaja	Heavy frame, smooth/moist skin, thick hair, large eyes	Slow appetite/digestion, heavy sleep, high endurance, cold tolerance	Calm, loyal, deliberate, stable, resistant to change	Obesity, metabolic syndrome, respiratory congestion, hypothyroid
Vāta-Pittaja	Lean-medium, variable skin	Irregular-strong appetite, moderate energy	Creative + analytical, anxious + competitive	Combination: inflammatory + neurological
Pitta-Kaphaja	Medium-heavy, warm skin	Strong-slow appetite, sustained energy	Assertive + stable, determined	Combination: metabolic + inflammatory
Vāta-Kaphaja	Variable frame, dry/moist mix	Irregular-slow appetite, variable energy	Anxious + withdrawn, creative + slow	Combination: neurological + metabolic
Sama	Proportionate, balanced features	Regular appetite, stable energy, balanced sleep	Balanced temperament, adaptable	Lowest susceptibility; best health outcomes

2.3 Challenges in Traditional Prakṛti Assessment

Despite the comprehensive classical framework, traditional Prakṛti assessment faces several methodological challenges that have limited its scientific acceptance and clinical scalability. These include: moderate inter-rater reliability (different practitioners classify the same individual differently, with Cohen's kappa typically 0.4–0.65); questionnaire dependency (most modern assessments use self-report questionnaires subject to response bias, social desirability, and cultural interpretation); the subjective nature of physical examination (skin quality, body frame, and facial features are assessed through visual and tactile inspection without objective measurement); and the lack of a universally accepted gold standard for Prakṛti classification (no single validated tool, biomarker panel, or reference standard exists) [4,5,7].

These challenges create the precise conditions under which AI and ML technologies can provide transformative value: pattern recognition in complex multi-dimensional datasets, objective classification from sensory data, standardisation through algorithmic consistency, and scalability through digital deployment.

3. ARTIFICIAL INTELLIGENCE IN HEALTHCARE: RELEVANCE TO PRAKṚTI

Artificial Intelligence encompasses a broad family of computational techniques that enable machines to learn patterns from data and make predictions or classifications without explicit programming. Machine Learning (ML), a subset of AI, uses algorithms that improve their performance through exposure to training data. Deep Learning (DL), a subset of ML, employs multi-layered neural networks capable of learning hierarchical representations from raw data — making it particularly suited to complex, unstructured inputs such as images, waveforms, and free text [8].

The healthcare applications of AI have expanded rapidly, with demonstrated success in medical image analysis (radiology, dermatology, pathology), clinical decision support, drug discovery, genomic analysis, and predictive diagnostics. For Āyurvedic Prakṛti assessment, AI is applicable across multiple modalities:

Structured data: Questionnaire responses, clinical measurements, demographic data → classification using traditional ML algorithms (SVM, Random Forest, Gradient Boosting, Neural Networks).

Signal data: Pulse waveforms, heart rate variability → sequence classification using CNNs, LSTMs, and transformer architectures.

Image data: Facial photographs, tongue images, body habitus → image classification using convolutional neural networks and transfer learning.

Genomic data: SNP profiles, gene expression arrays, metabolomic panels → high-dimensional classification using ensemble methods and deep learning.

Text data: Classical textual descriptions, clinical notes → NLP-based feature extraction and knowledge graph construction.

Multi-modal fusion: Integration of two or more data modalities for comprehensive, robust classification.

4. AI-BASED PRAKṚTI CLASSIFICATION: QUESTIONNAIRE AND CLINICAL DATA MODELS

4.1 Dataset Construction and Feature Engineering

The most widely explored AI approach to Prakṛti classification uses structured questionnaire data as input. Validated Prakṛti assessment instruments — including the CCRAS Prakriti Assessment Proforma, the NIAM (National Institute of Ayurvedic Medicine) tool, the Prakriti analysis tool developed by Ayusoft (CDAC Pune), and various research-specific instruments — generate numerical or categorical response vectors across 30–100 questions covering physical, physiological, and psychological domains [9,10].

Feature engineering involves encoding categorical responses as numerical values, normalising continuous variables (height, weight, BMI, skin temperature), handling missing data through imputation, and reducing dimensionality through Principal Component Analysis (PCA) or feature selection algorithms. The target variable is the Prakṛti class — typically three-class (Vāta/Pitta/Kapha) or seven-class (including dual and Sama types) — labelled by expert Āyurvedic clinicians [9,10].

4.2 Machine Learning Algorithms Applied

Multiple ML algorithms have been applied to Prakṛti classification from questionnaire data:

Support Vector Machines (SVM): SVMs with radial basis function (RBF) kernels have been among the most frequently used classifiers, achieving reported accuracies of 78–89% for three-class Prakṛti discrimination. SVMs perform well with moderate-sized datasets and handle the relatively high-dimensional feature space of questionnaire data effectively [9,11].

Random Forest (RF): Ensemble tree-based methods, particularly Random Forest, have demonstrated strong performance (80–93% accuracy) with the additional benefit of providing feature importance rankings — identifying which questionnaire items are most discriminative for Prakṛti classification. This information is clinically valuable for developing shorter, more efficient screening instruments [10,11].

Artificial Neural Networks (ANN): Feedforward neural networks with one or two hidden layers have achieved 82–91% classification accuracy, with their non-linear decision boundary capability providing advantages for complex, overlapping Prakṛti phenotypes. However, ANNs require larger training datasets and are more prone to overfitting on small samples [11,12].

Gradient Boosting (XGBoost, LightGBM): Modern gradient boosting frameworks have recently been applied with promising results (85–93%), offering strong performance, built-in regularisation, and interpretability through feature importance and SHAP (SHapley Additive exPlanations) values [12].

k-Nearest Neighbours (k-NN) and Naïve Bayes: Simpler algorithms have been used as baseline comparators, generally achieving lower accuracy (65–78%) but useful for understanding the difficulty of the classification task and establishing minimum performance thresholds [9].

4.3 Ayusoft: A Landmark Decision Support Tool

The Ayusoft system, developed by the Centre for Development of Advanced Computing (CDAC) Pune in collaboration with CCRAS, represents one of the most comprehensive computational Prakṛti assessment tools developed to date. It incorporates a standardised questionnaire, an algorithmic scoring and classification engine, and clinical decision support features. Ayusoft processes responses through a weighted scoring algorithm calibrated against expert clinical assessment, producing Prakṛti classification with visual representation of Doṣic proportions [10]. While not a machine learning system in the strict sense, Ayusoft established the foundational infrastructure for digitised Prakṛti assessment that subsequent AI-based systems have built upon.

5. AI-BASED PULSE WAVEFORM ANALYSIS FOR PRAKṚTI CLASSIFICATION

5.1 Sensor Technologies and Signal Acquisition

Pulse waveform analysis represents a particularly compelling AI application because it directly digitalises the traditional Nāḍī Parīkṣā — converting the experienced Vaidya's qualitative palpatory assessment into objective, quantifiable, and algorithmically classifiable signal data. Sensor technologies employed include:

Piezoelectric transducers: Convert mechanical pulse pressure into electrical signals with high sensitivity and temporal resolution. Multi-element arrays can be designed to replicate the three-finger technique, simultaneously capturing waveforms at the Vāta, Pitta, and Kapha positions [13].

Photoplethysmography (PPG): Optical sensors measure volumetric changes in blood vessels through light absorption and reflection. PPG is the technology underlying pulse oximeters and many smartwatches, making it the most scalable and commercially available option [14].

Force-sensitive resistors (FSR) and capacitive sensors: Low-cost alternatives that measure pressure changes at the radial artery with moderate resolution [13].

5.2 Feature Extraction from Pulse Waveforms

Signal processing of radial pulse waveforms generates a rich feature set for ML classification:
Time-domain features: Pulse rate, pulse width, rise time (systolic upstroke), fall time (diastolic downstroke), dicrotic notch position, peak amplitude, pulse area (systolic and diastolic), and inter-pulse interval variability.

Frequency-domain features: Fast Fourier Transform (FFT) spectral coefficients, dominant frequency, spectral centroid, spectral energy distribution, and harmonic analysis.

Wavelet-domain features: Discrete Wavelet Transform (DWT) coefficients at multiple scales, capturing both frequency and time-localisation information that is particularly relevant for characterising the transient features of pulse morphology. Statistical features: Mean, variance, skewness, kurtosis, and entropy of the pulse signal — providing aggregate descriptors of waveform shape and regularity.

5.3 Deep Learning Architectures for Pulse Classification

Convolutional Neural Networks (CNN): 1D-CNNs applied to raw pulse waveform data have demonstrated the ability to learn discriminative features directly from the signal without manual feature engineering. CNN architectures with multiple convolutional and pooling layers followed by fully connected classification layers have achieved 78–90% accuracy for Doṣic pulse classification [14,15].

Long Short-Term Memory Networks (LSTM): LSTM architectures, designed for sequential data, capture temporal dependencies in pulse waveform sequences — learning patterns in how the pulse evolves over successive beats. LSTM-based classifiers have achieved 75–88% accuracy and are particularly effective for capturing the irregular, variable rhythm characteristic of Vāta pulse [14,15].

Hybrid CNN-LSTM models: Combined architectures using CNN layers for local feature extraction and LSTM layers for temporal sequence modelling have shown superior performance (82–92%) to either architecture alone, as they capture both morphological (shape) and rhythmic (temporal) information [15].

Transformer-based models: Attention-based transformer architectures, originally developed for NLP, have recently been applied to physiological signal classification with promising preliminary results. Self-attention mechanisms allow the model to focus on the most informative segments of the pulse waveform, potentially improving classification of subtle Doṣic differences [16].

6. AI-BASED FACIAL AND TONGUE IMAGE ANALYSIS

6.1 Facial Image Classification

Classical Prakṛti assessment relies significantly on visual evaluation of facial features — bone structure (wide vs narrow), skin quality (dry, oily, warm), eye characteristics (small/dry, sharp/reddish, large/moist), lip morphology, and overall facial proportions. These visual features are directly amenable to computer vision analysis using convolutional neural networks [17].

Transfer learning using pre-trained deep CNN architectures — VGG16, VGG19, ResNet50, InceptionV3, and EfficientNet — has been applied to facial image datasets labelled with expert Prakṛti assessments. These models, pre-trained on millions of general images (ImageNet), are fine-tuned on Prakṛti-labelled facial image datasets. Published studies report 65–85% classification accuracy for three-class discrimination, with performance improving significantly with dataset size. The primary challenges include: controlling for lighting, angle, and background variation; demographic and ethnic diversity in training data; small dataset sizes (typically 200–1000 images); and the inherent difficulty of distinguishing Prakṛti from age-related, lifestyle-related, and disease-related facial changes [17,18].

6.2 Tongue Image Analysis (Jihvā Parīkṣā)

Tongue examination (*Jihvā Parīkṣā*) is a key component of Aṣṭavidha Parīkṣā, with tongue colour, coating, shape, moisture, and surface features varying systematically across Doṣic types and disease states. The Vāta tongue is described as dry, rough, cracked, and thin; the Pitta tongue as red, inflamed, with yellow coating; and the Kapha tongue as pale, swollen, with white/thick coating [1,3].

Computer vision-based tongue analysis using colour space segmentation (RGB, HSV, L*a*b*), texture feature extraction (Local Binary Patterns, Gabor filters), and deep CNN classification has been applied to tongue images for both Prakṛti assessment and disease classification. Preliminary studies report 60–80% accuracy for Doṣic classification from tongue images, with colour features being the most discriminative. Integration of tongue analysis with facial analysis in multi-modal frameworks shows incremental improvement over either modality alone [18,19].

7. GENOMIC AND MULTI-OMICS DATA INTEGRATION WITH AI

7.1 Prakṛti Genomics: The Molecular Validation

The landmark study by Prasher et al. (2008) in the Journal of Translational Medicine demonstrated that individuals classified into extreme Prakṛti types (Vāta, Pitta, Kapha) by expert Āyurvedic clinicians show significantly different whole-genome expression profiles, particularly in genes governing immunity, metabolism, and inflammatory response [20]. Subsequent studies by Govindaraj et al. (2015) identified Prakṛti-associated SNP (single nucleotide polymorphism) profiles in a genome-wide association study [21]. Rotti et al. (2014) reported Prakṛti-specific metabolomic signatures and platelet transcriptome differences [22]. These studies collectively establish that Prakṛti classification captures genuine molecular-level biological variability — providing the scientific justification for AI-based classification approaches.

7.2 AI/ML for Genomic Prakṛti Classification

High-dimensional genomic data — comprising thousands of gene expression values, hundreds of thousands of SNPs, and thousands of metabolomic features — is inherently suited to ML analysis. Supervised learning algorithms applied to Prakṛti-labelled genomic data include:

Penalised regression (LASSO, ElasticNet): These methods perform simultaneous feature selection and classification, identifying the minimal set of genomic markers that best discriminate Prakṛti types. LASSO-selected gene panels show strong discriminatory power while reducing dimensionality from thousands to tens of features [20,23].

Random Forest and Gradient Boosting: Ensemble tree methods handle high-dimensional genomic data effectively, providing both classification and feature importance rankings. Gene sets identified as most discriminative for Prakṛti overlap significantly with genes involved in metabolism, immunity, and cellular stress response [21,23].

Deep Neural Networks: Deep autoencoders for unsupervised feature learning from genomic data, followed by supervised classification layers, have been explored for multi-omics integration — combining gene expression, SNP, and metabolomic data into unified latent representations for Prakṛti classification [23].

Pharmacogenomic implications: Prakṛti-associated differences in cytochrome P450 enzyme gene polymorphisms (CYP2C19, CYP2D6, CYP3A4) suggest that AI-based Prakṛti classification could predict drug metabolism phenotypes (poor, intermediate, extensive, ultrarapid metaboliser) — enabling Āyurvedic pharmacogenomics [24].

8. NATURAL LANGUAGE PROCESSING FOR CLASSICAL TEXT ANALYSIS

Natural Language Processing (NLP) offers a complementary AI approach for Prakṛti research: systematic computational analysis of classical Āyurvedic textual sources. The corpus of classical Prakṛti descriptions — spanning Charaka Samhitā, Suśruta Samhitā, Aṣṭāṅgahṛdayam, and commentaries — contains thousands of descriptive terms, associations, and clinical observations that can be extracted, structured, and quantified through NLP techniques [25].

Named Entity Recognition (NER): Identification and extraction of Āyurvedic clinical terms (Doṣa names, Prakṛti types, symptoms, herbs, formulations) from Sanskrit/Hindi/English texts.

Knowledge Graph Construction: Mapping relationships between Prakṛti types, physical features, disease associations, dietary recommendations, and therapeutic interventions into structured knowledge graphs that can support clinical decision systems.

Sentiment and Feature Analysis: Extracting and quantifying the qualitative descriptors (dry, hot, heavy, sharp, slow, etc.) associated with each Prakṛti type to generate numerical feature vectors from textual descriptions.

NLP-based text mining of classical Āyurvedic literature can generate structured, computational representations of traditional knowledge that serve as training labels, validation benchmarks, and clinical rules for AI-based Prakṛti systems. This represents a bridge between classical scholarly analysis and modern data science [25].

9. WEARABLE SENSORS, IOT, AND CONTINUOUS PRAKṚTI MONITORING

The convergence of wearable biosensor technology, Internet of Things (IoT) connectivity, and cloud-based AI creates the possibility of continuous, real-time Prakṛti-relevant physiological monitoring. Modern wearable devices can capture:
Pulse waveform: PPG sensors in smartwatches continuously capture pulse morphology, heart rate, and heart rate variability (HRV) — data directly relevant to Doṣic assessment.

Skin parameters: Electrodermal activity (skin conductance), skin temperature, and ambient humidity sensors capture data relevant to Doṣic skin characteristics (dry/cold for Vāta, warm/oily for Pitta, cool/moist for Kapha).
Activity and sleep patterns: Accelerometer and gyroscope data capture movement patterns, exercise intensity, and sleep quality — parameters that vary systematically with Prakṛti type.

Body composition: Bioimpedance analysis (BIA) sensors estimate body fat percentage, lean mass, and hydration status — metrics that correlate with constitutional morphology.

Edge AI — lightweight neural network models deployed directly on wearable devices — enables real-time, on-device Doṣic inference from sensor data, with periodic cloud synchronisation for longitudinal tracking and advanced multi-modal analysis. This architecture supports continuous Prakṛti monitoring that extends assessment beyond the clinical encounter into the patient's daily life [26,27].

A prototype Āyurvedic digital twin — a computational model of an individual's constitutional profile, continuously updated from wearable data and enriched with genomic, dietary, and clinical information — represents a long-term vision for AI-enabled personalised Āyurveda [27].

10. MULTI-MODAL DATA FUSION FOR COMPREHENSIVE PRAKṚTI CLASSIFICATION

The most robust and clinically comprehensive AI-based Prakṛti assessment will require fusion of multiple data modalities — combining questionnaire responses, pulse waveform features, facial/tongue image analysis, genomic data, and wearable sensor data into a unified classification framework [28].

Early fusion: Concatenating feature vectors from all modalities into a single high-dimensional input vector for a unified classifier. Simple but may lose modality-specific information.

Late fusion: Training separate classifiers for each modality and combining their predictions through voting, stacking, or weighted averaging. Preserves modality-specific expertise but may miss cross-modal interactions.

Intermediate/deep fusion: Using multi-branch deep neural networks where each branch processes one modality, with shared hidden layers that learn cross-modal representations before final classification. This approach offers the best theoretical performance but requires large, well-annotated multi-modal datasets [28].

The development of standardised, multi-modal Prakṛti datasets — with simultaneous questionnaire, pulse, facial image, tongue image, and genomic data collected from the same subjects with expert clinical labelling — is the single most critical infrastructure requirement for advancing multi-modal AI-based Prakṛti assessment.

11. CHALLENGES, LIMITATIONS, AND ETHICAL CONSIDERATIONS

Data Challenges

Small dataset sizes: Most published studies use datasets of 100–1000 subjects, insufficient for training deep learning models and limiting generalisability. Population-level Prakṛti datasets (10,000+ subjects) with multi-modal data are needed.
Class imbalance: Dual-Doṣic and Sama Prakṛti types are less represented than extreme mono-Doṣic types, creating class imbalance that biases classifiers. Techniques such as SMOTE (Synthetic Minority Oversampling), class weighting, and focal loss can mitigate this.

Gold standard labelling: The absence of a universally accepted reference standard for Prakṛti classification means that training labels are inherently subjective. Multi-expert consensus labelling, inter-rater reliability assessment, and iterative label refinement are needed.

Methodological Challenges

External validation: Most studies report only internal cross-validation accuracy. External validation on independent, geographically and ethnically diverse populations is essential but rarely performed.
Interpretability: Black-box deep learning models provide high accuracy but limited clinical interpretability. Explainable AI (XAI) techniques — SHAP values, attention visualisation, gradient-weighted class activation mapping (Grad-CAM) — must be integrated to make AI classifications clinically meaningful and acceptable to Āyurvedic practitioners.
Overfitting risk: Small datasets and high-dimensional features create overfitting risk. Rigorous regularisation, dropout, and cross-validation strategies are essential.

Ethical and Regulatory Considerations

Patient privacy: Facial images, genomic data, and continuous wearable data raise significant privacy concerns. Data

anonymisation, informed consent, and compliance with data protection regulations (GDPR, India's DPDP Act) are mandatory.
Cultural sensitivity: AI systems must be developed in partnership with traditional Āyurvedic practitioners to ensure that computational classifications respect and accurately represent classical knowledge rather than distorting it through algorithmic oversimplification.

Clinical deployment risks: Premature deployment of inadequately validated AI Prakṛti tools could lead to misclassification and inappropriate clinical decisions. Regulatory frameworks for digital Āyurvedic diagnostics are needed.
Bias and equity: Training datasets that overrepresent specific demographics (age groups, geographic regions, socioeconomic strata) will produce biased classifiers. Representative, diverse datasets are essential for equitable deployment.

12. FUTURE DIRECTIONS AND TRANSLATIONAL POTENTIAL

The convergence of AI and Prakṛti assessment opens multiple high-impact translational pathways:
Standardised digital assessment platforms: Cloud-based, AI-powered Prakṛti assessment tools accessible via smartphone applications, integrating questionnaire, camera-based facial/tongue analysis, and smartwatch-derived pulse data, deployable through platforms such as VaidyaSetu for telemedicine-enabled Āyurvedic consultation.

Āyurvedic pharmacogenomics: Integration of AI-predicted Prakṛti types with CYP450 pharmacogenomic profiles for personalised drug selection and dosing — bridging classical Āyurvedic individualisation with modern pharmacogenomics.
Preventive health screening: Population-level Prakṛti screening using AI tools to identify individuals at heightened risk for specific disease categories, enabling targeted preventive interventions (Svāsthavṛtta).

Clinical trial stratification: AI-based Prakṛti classification as a stratification variable in Āyurvedic clinical trials, reducing heterogeneity and improving statistical power for treatment effect detection.

Large-scale collaborative datasets: Establishment of multi-institutional, multi-national Prakṛti biobanks with standardised clinical labelling, multi-modal data collection (questionnaire, pulse, imaging, genomics), and open-access data sharing protocols — analogous to the UK Biobank model but designed for Āyurvedic phenotyping.

Federated learning: Privacy-preserving AI training across multiple clinical sites without centralised data collection — enabling collaborative model development while protecting patient data.

Reinforcement learning for clinical decision support: AI systems that learn optimal Āyurvedic treatment strategies for each Prakṛti type through interaction with clinical outcome data over time.

13. CONCLUSION

The application of Artificial Intelligence to Prakṛti assessment represents one of the most promising convergence points between traditional Āyurvedic knowledge and modern computational science. Classical Āyurveda established a sophisticated, empirically grounded framework for constitutional classification over two millennia ago — a framework that has been independently validated at the molecular level through genomic, metabolomic, and transcriptomic studies. AI and ML technologies now offer the tools to objectify, standardise, and scale this classification through multiple computational modalities: questionnaire-based ML classifiers, pulse waveform deep learning, facial and tongue image analysis, genomic data mining, NLP-based textual analysis, and wearable sensor-driven continuous monitoring.

Current evidence demonstrates feasibility across all these modalities, with classification accuracies ranging from 60% to 93% depending on the modality, algorithm, and dataset. The field is at an early but rapidly advancing stage, with critical next steps including: development of large, diverse, multi-modal, expert-labelled datasets; external validation across populations; multi-modal data fusion architectures; explainable AI for clinical interpretability; standardised regulatory frameworks; and responsible, practitioner-partnered deployment strategies.

The successful integration of AI-based Prakṛti assessment into clinical practice would represent a paradigm shift — transforming Āyurvedic personalised medicine from a subjective, expert-dependent art into an objective, reproducible, scalable science without losing the depth and nuance of the classical tradition. This integration positions Āyurveda not as an archaic alternative but as a data-rich, philosophically coherent complement to genomics-driven precision medicine — united by the shared conviction that effective healthcare must be individualised to the unique biological constitution of each patient.

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