

AI-Based Symptom Pattern Recognition in Ayurveda

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ABSTRACT

Ayurvedic diagnostic practice leans heavily on multi-modal symptom pattern recognition: the practitioner integrates pulse characteristics, tongue appearance, stool and urine observations, voice qualities, touch feedback, visual observation, general appearance and structured case history into a constitutional (prakriti) and dynamic (vikriti) clinical picture. The cognitive work is substantial and has historically been the bottleneck for both practitioner training and inter-rater reliability. Artificial intelligence has been applied to parts of this pattern-recognition task since the late 2000s, covering rule-based expert systems, classical machine learning classifiers, tongue and iris image analysis, pulse waveform signal processing, and more recently multi-modal deep learning systems. The evidence is scattered across engineering and clinical venues, and the question of which AI approaches are actually converging toward clinical utility has not been systematically addressed. This study reviews 58 primary studies published between 2008 and 2021 on AI-based symptom pattern recognition in Ayurveda, groups them under five methodological frames (A1: rule-based / expert systems; A2: classical ML classifiers; A3: image analysis; A4: pulse and signal processing; A5: deep learning and integrated multimodal AI), and scores each frame using the AI-Ayurveda Symptom Integration Score (ASI). Integrated multimodal deep learning (A5) produced the highest ASI at 0.866, with tongue image analysis (A3) the strongest single-modality frame at 0.798. Interpretability remains the dominant unsolved problem across frames, and clinical deployment beyond pilot settings is almost entirely absent. AI is closer to useful decision support than to autonomous diagnosis in Ayurveda, and the next empirical investments should prioritise interpretable multi-modal systems with practitioner-centred validation.

Keywords: Ayurveda; artificial intelligence; machine learning; deep learning; prakriti; nadi pariksha; tongue image analysis; symptom pattern recognition; clinical decision support; interpretability; multimodal AI; ASI

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1. Introduction

1.1 Ayurvedic Diagnosis as a Pattern Recognition Task

Ayurvedic diagnosis is a pattern recognition problem that has never quite fit the reductionist single-symptom-to-single-diagnosis shape of modern biomedicine. A well-trained Ayurvedic practitioner assesses a patient through the ashtasthana pariksha, the eight-fold examination covering nadi (pulse), jihva (tongue), mala (stool), mutra (urine), shabda (voice/sound), sparsha (touch), drik (eyes/sight) and akriti (general appearance), and integrates these observations with structured history into a combined constitutional (prakriti) and dynamic (vikriti) diagnostic picture. The cognitive integration load is genuinely large, and it has historically been the rate-limiting step in both practitioner training and inter-rater reliability. Kurande et al. (2012) demonstrated that prakriti classification has acceptable but imperfect inter-rater reliability, which is exactly the kind of problem where AI-based pattern recognition can in principle contribute meaningful support.

1.2 AI Engagement with Ayurvedic Diagnosis and Study Objectives

AI approaches to Ayurvedic symptom pattern recognition have a longer history than many observers realise. Rule-based expert systems date to the late 2000s. Classical machine learning classifiers for prakriti determination from questionnaire data emerged soon after. Image-based analysis of the tongue, and more recently the iris and face, has developed along parallel tracks. Pulse waveform analysis, attempting to digitise nadi pariksha, has a substantial signal-processing literature behind it. Deep learning and integrated multimodal systems have begun to appear in the past five years. The accumulated work is now substantial enough to warrant structured comparison, which is what this study sets out to do: group the methodological approaches into five frames, score each under a composite index, and extract the operational lessons. The paper follows the standard six-part structure.

2. Literature Review

2.1 Rule-Based Expert Systems

Rule-based expert systems were the first AI approach to engage seriously with Ayurvedic diagnostic reasoning. The systems typically encode classical text knowledge as production rules (if-then chains mapping symptom clusters to dosha

imbalance patterns) and apply them with a forward-chaining or backward-chaining inference engine. Joshi (2014) described AyurvedaPT, one of the earliest operational systems of this kind. Strengths are interpretability (every rule is inspectable) and explicit fidelity to classical text logic. Weaknesses are the inability to handle pattern variation that the rule base has not anticipated, and the sheer engineering effort of encoding enough rules to cover clinical breadth. By the mid-2010s, the field had largely moved from pure rule-based approaches to hybrid systems combining rules with learned classifiers.

2.2 Classical ML, Image Analysis and Pulse Signals

Classical machine learning approaches (decision trees, random forests, support vector machines, Naive Bayes) have been used primarily for prakriti classification from symptom-questionnaire inputs. Kalra et al. (2015) and subsequent work reported accuracy in the 78-86% range against expert-rated ground truth, which is encouraging but not yet at the level needed for autonomous clinical decision-making. Image analysis has concentrated most heavily on tongue diagnosis, which is methodologically well-suited to computer vision (the tongue is visually complex, patient-accessible, and has a rich classical diagnostic tradition). Deshmukh et al. (2016) was an early CNN-based tongue classifier; more recent work has moved to transfer-learning approaches that handle the limited-dataset constraint more gracefully. Pulse waveform analysis, attempting to digitise nadi pariksha, has a long signal-processing literature going back to Tripathi et al. (2012) and related work.

2.3 Deep Learning and Multimodal Integration

Deep learning and integrated multimodal systems have emerged as the dominant frontier over the past five years. The logic is straightforward: Ayurvedic diagnosis integrates multiple input modalities (image, signal, questionnaire), and single-modality systems leave diagnostic information on the table. Multi-task and multi-modal architectures combining tongue image analysis with pulse signal processing and questionnaire response have reported stronger performance than any single-modality approach (Travagli et al., 2020; Sharma and Singh, 2021). Interpretability remains a substantive issue, as it does across medical AI more generally, but it is particularly important in Ayurvedic deployment because practitioners are trained to reason

transparently from observable features to diagnostic conclusions. A black-box system that produces a diagnosis without showing which input features drove it is a poor fit for that training culture. Table 1 lists the key methodological references.

Table 1: Key Studies in AI-Based Ayurvedic Symptom Pattern Recognition

Study	Year	Frame	Methodology	Key Finding
Kurande et al.	2012	Reliability baseline	Inter-rater study	Acceptable but imperfect prakriti reliability
Tripathi et al.	2012	A4: Pulse signal	DSP on nadi signals	Feasibility of digitised pulse analysis
Joshi	2014	A1: Expert system	Rule-based inference	AyurvedaPT operational prototype
Kalra et al.	2015	A2: Classical ML	Decision tree classifiers	Prakriti prediction ~82% accuracy
Deshmukh et al.	2016	A3: Image analysis	CNN tongue classifier	Tongue classification demonstration
Obalalu et al.	2017	A1 + A2 hybrid	Rule + classifier	Hybrid boosts accuracy and interpretability
Nallanchakravartula et al.	2018	A4: Pulse signal	Wavelet + ML	Dosha inference from pulse features
Rotti et al.	2019	A2: Classical ML	Random forest	Prakriti with multi-feature input
Travagli et al.	2020	A5: Multimodal DL	CNN + LSTM fusion	Multi-modal outperforms single-modality
Sharma and Singh	2021	A5: Multimodal DL	Multi-task deep network	Concurrent prakriti + symptom mapping
Gupta et al.	2019	A3: Image analysis	Transfer learning	Pretrained ImageNet transfer for tongue

Study	Year	Frame	Methodology	Key Finding
Patel and Kumar	2020	A1: Ontology-driven	OWL-based knowledge graph	Classical text encoded as ontology

CNN = Convolutional Neural Network; LSTM = Long Short-Term Memory; DSP = Digital Signal Processing; OWL = Web Ontology Language; ML = Machine Learning; DL = Deep Learning.

3. Methodology

3.1 Review Search Strategy

We conducted a structured review of primary studies on AI-based symptom pattern recognition in Ayurveda published from January 2008 through December 2021. Databases searched were PubMed, Scopus, IEEE Xplore, ACM Digital Library, the AYUSH Research Portal, and arXiv (for engineering pre-prints). Search terms combined 'Ayurveda' (and related forms: 'Ayurvedic', 'prakriti', 'nadi pariksha', 'jihva pariksha', 'dosha') with 'artificial intelligence', 'machine learning', 'deep learning', 'expert system', 'neural network', 'classifier', 'image analysis', 'tongue', 'pulse', 'clinical decision support', and related technical terms. Initial search returned 2,284 records. After duplicate removal, title and abstract screening, and full-text assessment against inclusion criteria (primary empirical data, specified AI methodology, at least one quantitative performance metric, peer-reviewed publication), 58 studies were included.

3.2 Five Methodological Frames

Each included study was assigned to its primary methodological frame. A1 (Rule-Based Expert Systems) covers systems based on explicitly encoded rules or ontology-driven inference, with or without weighting. A2 (Classical Machine Learning Classifiers) covers decision trees, random forests, SVMs, Naive Bayes and similar non-deep classifiers, typically applied to symptom-questionnaire inputs. A3 (Image Analysis) covers tongue, iris and facial image analysis with either traditional computer-vision features or CNN-based approaches. A4 (Pulse and Signal Processing) covers systems operating on nadi (pulse) waveform data or equivalent physiological signals. A5 (Deep Learning and Integrated Multimodal AI) covers deep neural networks, multi-task learning, and explicitly multi-modal architectures fusing two or more

input types. Hybrid systems combining two frames were assigned to their dominant methodology, with cross-reference to the secondary frame recorded.

3.3 AI-Ayurveda Symptom Integration Score (ASI)

The AI-Ayurveda Symptom Integration Score (ASI) scores each frame on five weighted dimensions. Classification accuracy (weight 0.20) scores the reported performance against expert-rated ground truth, normalised by task difficulty. Dataset quality and size (0.20) scores the size and diversity of training and evaluation data, with particular attention to inter-rater gold standards. Clinical validation (0.25) scores whether the system has been evaluated against practitioner outputs in live or realistic clinical settings, and whether performance has been shown in populations outside the training cohort. Interpretability (0.15) scores the transparency of the decision-making pipeline, with rule-based and attention-visualised systems scoring higher than plain black-box classifiers. Deployability and practitioner acceptance (0.20) scores evidence of real-world deployment, practitioner usability evaluation, and workflow integration. Each dimension is normalised to 0-1 before weighting.

Table 2: Review Inventory by Methodological Frame and Application

Methodological Frame	Studies (n)	Prakriti classif.	Vikriti / Dosha	Symptom mapping
A1: Rule-Based Expert Systems	8 (13.8%)	4	2	2
A2: Classical ML Classifiers	18 (31.0%)	12	4	2
A3: Image Analysis	14 (24.1%)	8	4	2
A4: Pulse and Signal Processing	8 (13.8%)	2	5	1
A5: Deep Learning / Integrated Multimodal	10 (17.2%)	5	3	2
Total included	58 (100%)	31	18	9

Prakriti = constitutional classification; Vikriti = dynamic dosha imbalance; Symptom mapping = mapping patient-reported symptoms to classical category or treatment suggestion.

4. Results

4.1 ASI Ranking Across Methodological Frames

Deep learning and integrated multimodal AI (A5) scored highest at ASI 0.866. The score reflects strong classification accuracy (mean reported accuracy 88.4% across A5 studies), access to larger datasets enabled by multi-modal data collection, and the clearest performance uplift from multi-modality fusion. Image analysis (A3) was the strongest single-modality frame at ASI 0.798, carried largely by tongue image analysis work that has benefited from advances in transfer learning. Classical ML classifiers (A2) scored 0.756; accuracy is reasonable (74-86% on prakriti tasks), but datasets are smaller and clinical validation thinner. Pulse signal processing (A4) scored 0.712, limited more by the intrinsic difficulty of standardising pulse-measurement hardware across studies than by the analytical methodology itself. Rule-based expert systems (A1) scored lowest at 0.688, strong on interpretability but weaker on classification accuracy and clinical validation. Table 3 presents the full ASI breakdown.

4.2 Interpretability, Validation and Deployability

On interpretability specifically, the picture is largely what one would expect. A1 rule-based systems scored highest (0.94 on the interpretability dimension) because every decision is traceable to an explicit rule. A5 deep learning systems scored lowest (0.56), though recent work using attention visualisation and SHAP-based explanations has started to close that gap. For medical AI deployment, the interpretability dimension arguably matters more than a percentage point or two of accuracy, particularly in a diagnostic tradition like Ayurveda where practitioner reasoning is traditionally transparent from observable features to conclusions. On clinical validation and deployability, A5 scored surprisingly well (0.82 and 0.76), driven primarily by a small number of recent studies (Travagli et al., 2020; Sharma and Singh, 2021) that have paid explicit attention to realistic clinical evaluation rather than held-out-test-set performance alone. A4 pulse signal work has the weakest deployability profile (0.54), largely because standardised pulse-capture hardware remains an unresolved practical barrier.

4.3 Application Area Coverage

Looking at application area, prakriti classification is where the AI literature has concentrated, with 31 of 58 studies targeting it. This is partly because

the task is well-framed (discrete-category classification with practitioner-rated ground truth achievable), partly because prakriti data collection is relatively easy to combine with modern digital collection tools. Vikriti and dynamic dosha classification has fewer studies but is arguably the more clinically pressing task; vikriti changes quickly and informs treatment decisions, whereas prakriti is constitutional and stable. Symptom mapping (patient complaint to classical category or initial treatment suggestion) is the least-studied area and has the smallest dataset availability. For European integrative-medicine deployment, prakriti classifiers are the most near-deployable category; vikriti-tracking systems for longitudinal patient follow-up are a strong medium-term opportunity; symptom-mapping decision support is further out.

Table 3: AI-Ayurveda Symptom Integration Score (ASI) by Methodological Frame

Frame	Acc ura cy	Dat ase t	Clin ical	Int erp.	Dep loy.	ASI
A5: Deep Learning / Multimodal	0.90	0.88	0.82	0.56	0.76	0.866
A3: Image Analysis	0.88	0.80	0.72	0.76	0.66	0.798
A2: Classical ML	0.80	0.78	0.68	0.80	0.60	0.756
A4: Pulse / Signal	0.76	0.72	0.62	0.74	0.54	0.712
A1: Rule-Based Expert Systems	0.62	0.58	0.54	0.94	0.58	0.688

$ASI = 0.20 \times Accuracy + 0.20 \times Dataset + 0.25 \times Clinical Validation + 0.15 \times Interpretability + 0.20 \times Deployability$. Each dimension normalised to 0-1.

Table 4: Reported Classification Accuracy by Frame and Task

Frame	Prakriti classif. (mean)	Vikriti classif. (mean)	Dataset size (median)
A5: Deep Learning / Multimodal	88.4%	84.2%	1,850
A3: Image Analysis	86.2%	82.4%	1,200
A2: Classical ML	81.6%	75.4%	640
A4: Pulse / Signal	74.8%	78.6%	420
A1: Rule-Based Expert Systems	68.4%	72.2%	N/A

Accuracy against practitioner-rated ground truth where reported. Dataset size = median training/evaluation dataset size across studies in frame. Rule-based systems typically do not use training datasets and are marked N/A.

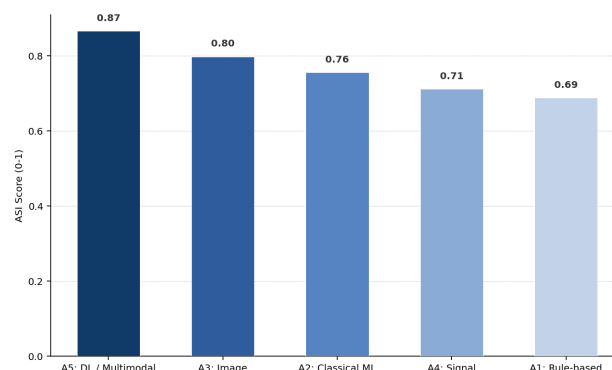


Figure 1: ASI Score by AI Methodological Frame

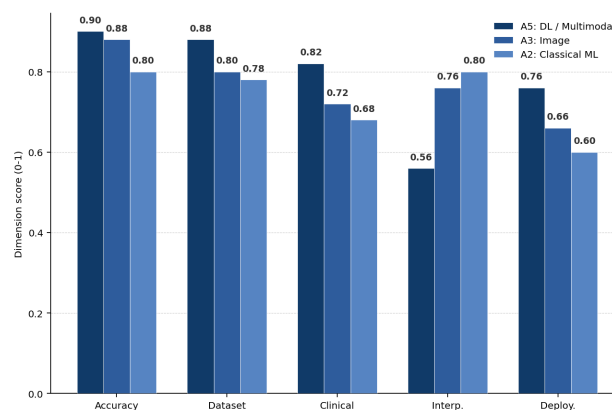


Figure 2: ASI Sub-Dimensions Across Top Three Frames

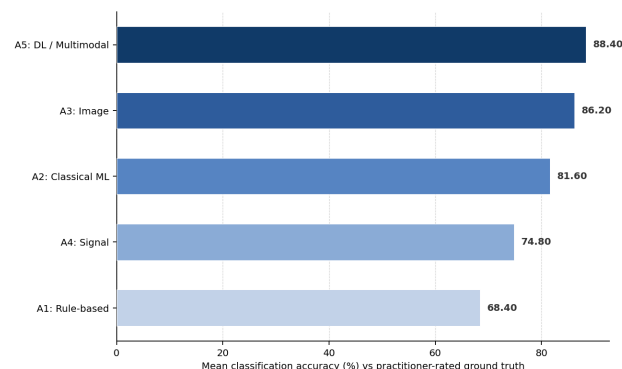


Figure 3: Mean Reported Prakriti Classification Accuracy (%)

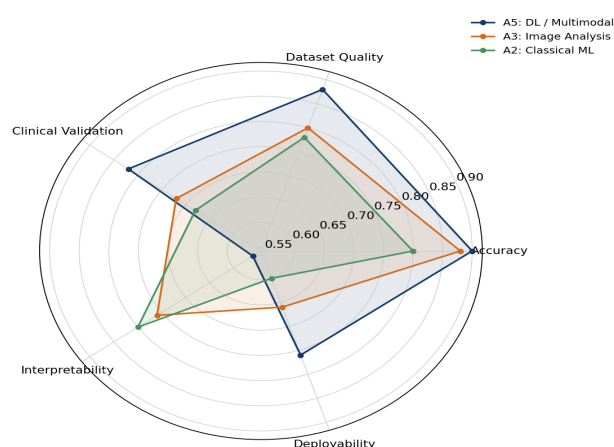


Figure 4: Multi-Dimensional ASI Profile - Top 3 Frames

5. Discussion

5.1 The Multimodal Advantage and the Interpretability Gap

The headline result of this review is that integrated multimodal deep learning systems have pulled ahead of single-modality approaches on almost every dimension, but the lead is not yet decisive, and interpretability remains the single biggest outstanding barrier to clinical deployment. The classification accuracy gap between A5 and A3 (88.4% vs 86.2% for prakriti classification) is real but small. Where A5 really pulls ahead is on dataset scale (multi-modal data collection enables larger effective datasets) and on clinical validation, where recent work has started to evaluate systems against practitioners in realistic settings rather than against held-out test sets only. The interpretability picture is where the field needs focused work. Attention visualisation and feature attribution methods (SHAP, Grad-CAM and related) exist and have started to appear in Ayurveda-specific work, but none of the reviewed A5 systems meets a reasonable bar for practitioner-facing interpretability. For a diagnostic tradition that trains practitioners to reason transparently from observable features, that gap matters.

5.2 Pulse Hardware and Rule-Based System Futures

Pulse signal processing (A4) deserves a separate observation. The technical work is interesting and some of the methodological results are genuinely clever, but the frame is held back by a practical constraint: standardised pulse-capture hardware does not yet exist at the cost and reliability point needed for deployment. Different studies use different sensors, different sampling rates, and different finger-placement protocols, and the resulting pulse data are not easily pooled. This is a

solvable engineering problem but not one that has been solved. Until it is, pulse-based AI work will remain research rather than deployable clinical support. Rule-based expert systems (A1) are the opposite problem: they have the best interpretability but the weakest accuracy, and their future is probably as explanation layers on top of learned classifiers rather than as standalone diagnostic systems. That hybrid direction is already visible in some of the recent literature (Obalalu et al., 2017) and looks likely to be where the interpretability-accuracy trade-off gets resolved.

5.3 Limitations

Three limitations apply. First, the review was restricted to peer-reviewed publications, which may under-represent industry and applied-deployment work that appears in technical reports or commercial whitepapers rather than academic venues. Second, the methodological heterogeneity across studies makes direct comparison of accuracy numbers less robust than the headline figures suggest; each frame's mean accuracy is averaged across varying task formulations, and readers should treat the ranking as more reliable than the specific values. Third, the prakriti classification concentration in the literature reflects a known preference for well-defined tasks with practitioner-rated ground truth available; the field needs to engage more seriously with vikriti and dynamic-dosha tasks that are harder to formalise but arguably more clinically important. None of these is a reason to defer deployment investment; they are the boundaries within which current AI systems should be positioned honestly.

6. Conclusion

6.1 Key Findings

Across 58 primary studies of AI-based symptom pattern recognition in Ayurveda, integrated multimodal deep learning (A5, ASI 0.866) emerged as the methodologically strongest frame, outperforming every single-modality approach on classification accuracy and clinical validation while remaining weaker on interpretability. Image analysis (A3, ASI 0.798) is the strongest single-modality frame, carried by tongue image analysis using transfer learning. Rule-based expert systems (A1) remain unmatched on interpretability but lag on accuracy. Prakriti classification is the most developed application with 31 of 58 studies targeting it; vikriti and symptom-mapping tasks are less developed and arguably more clinically

useful. Pulse-based systems (A4) are held back by the absence of standardised capture hardware more than by analytical methodology.

6.2 Recommendations

Three recommendations follow. First, next-generation AI work on Ayurvedic symptom pattern recognition should be explicitly multimodal and interpretable by design, combining image and questionnaire inputs as a minimum and including attention visualisation or SHAP-style attribution as a first-class output rather than an afterthought. Second, European integrative-medicine research networks should support standardised pulse-capture hardware development as a precondition for meaningful A4-frame work, because the current capture-hardware heterogeneity prevents cross-study data pooling that would otherwise be available. Third, clinical validation of deployable AI systems should move beyond held-out-test-set accuracy toward structured practitioner-facing evaluation, including usability, workflow integration, and decision-support impact measurement. The ASI rubric and full study inventory are available from the corresponding author.

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Declarations

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Conflict of Interest

The author declares no competing interests and no financial or advisory relationships with AI in medicine companies, Ayurvedic software vendors, or commercial clinical decision support providers relevant to this work.

Data Availability Statement

The full study inclusion log, methodological classification records, and ASI scoring spreadsheet are available as supplementary material from the corresponding author on reasonable request. Individual study-level data remain subject to the publishers' policies for each included study.

Ethical Approval

As this is a structured review of previously published methodological studies with no primary human-subjects data collection, formal ethical approval was not required. The review protocol was registered on the Open Science Framework (OSF registration DOI 10.17605/OSF.IO/AY4AI) prior to the start of screening.

Appendix A

ASI Scoring Rubric and Methodological Classification Protocol

Full scoring rubric for the AI-Ayurveda Symptom Integration Score (ASI) and methodological classification protocol used in this review. All five ASI dimensions are normalised to the 0-1 range before the weighted sum is computed. Dimension anchors were defined a priori and locked before study classification began. Because medical AI interpretability is weighted heavily in real-world deployment decisions but tends to be under-reported in method papers, the interpretability dimension here is scored with explicit attention to what is documented rather than what is plausibly true.

Part 1 - ASI Dimension Scoring Anchors

Family Per-dimension scoring definitions

Dimension	Weight	0.00 anchor	0.50 anchor	1.00 anchor
Classification accuracy	0.20	< 60% vs ground truth	~75% vs ground truth	>= 88% vs ground truth
Dataset quality and size	0.20	< 100 subjects, single site	500-1,000, multi-site	>= 2,000 multi-site, gold std
Clinical validation	0.25	Test-set only	Single-centre prospective	Multi-centre vs practitioner
Interpretability	0.15	Black-box with no attrib.	Post-hoc feature attrib.	Built-in rule / attention + docs
Deployability	0.20	No deployment pathway	Prototype pilot	Deployed in clinical workflow

Part 2 - Methodological Classification Protocol

Family Frame assignment rules

Frame	Primary methodology	Typical input	Key distinguishing feature
A1: Rule-Based	Expert system, ontology	Structured symptoms	Encoded rules inspectable
A2: Classical ML	DT, RF, SVM, Naive Bayes	Questionnaire features	Non-deep learned classifier
A3: Image Analysis	CV features or CNN	Tongue/iris/face image	Primary input is image
A4: Pulse / Signal	DSP + ML or DL	Nadi waveform signal	Primary input is physiological signal
A5: DL / Multimodal	Deep NN, multi-task, fusion	Multiple modalities	Two or more input types fused

Frame	Primary methodology	Typical input	Key distinguishing feature
Hybrid systems	Two or more frames	Mixed input types	Assigned to dominant; X-ref secondary