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MULTIMODAL ARTIFICIAL INTELLIGENCE FOR AUTHENTICATION AND QUALITY ASSURANCE OF RASASHASTRA RAW MATERIALS: A REVIEW

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ABSTRACT
Rasashastra, the Ayurvedic branch of alchemy and herbo-mineral therapeutics, relies on raw materials, including metals, minerals, gemstones, and toxic herbs, which require rigorous authentication before processing. Adulteration, substitution, and misidentification pose safety risks to consumers. Current quality assurance methods (organoleptic, physicochemical, and chromatographic) are often destructive, time-consuming-, or require expert interpretation. Multimodal artificial intelligence integrates data from multiple analytical sources, including spectroscopy, imaging, elemental analysis, and traditional organoleptic parameters, to enable rapid and non-destructive authentication. This review examines existing analytical techniques for Rasashastra raw materials, evaluates AI models applied to similar pharmaceutical and food authentication tasks, and proposes a multimodal AI framework combining near-infrared- spectroscopy, laser-induced- breakdown spectroscopy, high-resolution-imaging, and machine learning classifiers (support vector machines, convolutional neural networks, ensemble methods). Performance metrics from comparable applications (accuracy, 92–98%; sensitivity, 89–96%) suggest feasibility. Validation pathways, regulatory considerations, and integration into good manufacturing practice workflows are also discussed. This framework offers a pathway toward objective, reproducible, and real-time- raw material authentication for Rasashastra manufacturing.

KEYWORDS: Multimodal artificial intelligence; Rasashastra; Raw material authentication; Quality assurance; Spectroscopy; Machine learning.

1. INTRODUCTION

Rasashastra, a specialized branch of Ayurveda, employs processed metals (e.g., *abrakha* – mica, *tamra* – copper, *loha* – iron), minerals (e.g., *gandhaka* – sulfur, *hingula* – cinnabar), and detoxified toxic herbs (shodhana) (e.g., vatsanabha–Aconitum ferox).[1]

Authentication of raw materials is the first critical step; substitution or adulteration with cheaper analogs (e.g., lead oxide instead of cinnabar) has led to adverse events.[2]

Traditional authentication relies on *lakshana* (organoleptic characteristics) – color, odor, taste, touch, and sound.[3]

Although valuable, this approach is subjective and requires decades of practitioner experience. Modern analytical methods, such as X-ray- fluorescence (XRF), inductively coupled plasma mass spectrometry (ICP-MS), high-performance thin-layer--chromatography (HPTLC), and Fourier-transform-infrared spectroscopy (FTIR), provide objective data.[4,5]

However, these techniques are often destructive, require sample preparation, and cannot be deployed on the manufacturing floor.

Artificial intelligence (AI), particularly machine learning, has transformed quality assurance in the food, herbal, and pharmaceutical industries.[6] Multimodal AI, which combines data from two or more analytical sources, improves classification accuracy by exploiting complementary information.[7] For example, spectroscopic fingerprints combined with image texture features can distinguish genuine *Swarna Bhasma* (gold ash) from counterfeit samples with high reliability.[8]

Currently, no published framework integrates multimodal AI specifically for the authentication of Rasashastra raw materials. This review synthesizes the available data on analytical methods for key Rasashastra raw materials, surveys AI applications in adjacent fields (herbal medicine authentication, mineral identification, and pharmaceutical raw material testing), and proposes a multimodal AI architecture tailored to Rasashastra manufacturing settings.

2. METHODS

PubMed, Scopus, and Ayush Research Portal were searched (2000–2025) for "Rasashastra," "raw material authentication," "metal identification," "mineral analysis," "AI authentication herbal," "multimodal machine learning quality control," "spectroscopy adulteration detection," and "NIR mineral classification" using Boolean operators. The inclusion criteria were as follows: original research reporting quantitative analytical data (XRF, ICP-MS, FTIR, NIR, Raman, HPTLC) for Rasashastra raw materials (metals, minerals, herbs); studies on AI or machine learning for the authentication of similar materials (herbal powders, mineral ores, pharmaceutical excipients); and publications describing multimodal data fusion for classification. The exclusion criteria were as follows: studies without numerical data, non-English- studies without translation, reviews without primary data, and conference abstracts without full methodology.

Reference lists were screened. Of 187 initial records, 53 met criteria. Data extraction covered raw material type, analytical method(s), AI model type, reported accuracy or sensitivity and sample size. The data were tabulated and synthesized narratively. The multimodal AI framework integrates sensor modalities (NIR, LIBS, imaging) and classifier architectures (SVM, CNN, random forest) based on validated performance in analogous authentication tasks.

3. RESULTS

3.1 Key Rasashastra raw materials and their authentication challenges

Table 1 lists the commonly used Rasashastra raw materials, primary adulterants, and conventional analytical methods.

Table 1: Rasashastra raw materials, adulterants, and analytical methods.

Raw Material	Common Adulterant	Primary Analytical Method	Reported Limit of Detection
Hingula (cinnabar, HgS)	Red lead oxide (Pb_3O_4)	XRF, ICP-MS	0.2% Pb[9]
Abrakha (biotite mica)	Synthetic mica, talc	XRD, FTIR	5% talc[10]
Gandhaka (sulfur)	Gypsum, calcium carbonate	DSC, elemental analysis	3% impurity[11]
Vatsanabha (Aconitum ferox)	Aconitum napellus (less potent)	HPTLC (aconitine)	0.05% w/w[12]
Tamra bhasma (copper ash)	Brass shavings, zinc oxide	AAS, SEM-EDS	2% Zn[13]
Shilajatu (bitumen)	Artificial bitumen, ash	UV-Vis, FTIR	Not standardized[14]

Current methods require offline sample preparation and skilled operators and cannot be deployed in real time. However, no consensus reference standard exists for Shilajatu.[14]

3.2 Single-modality AI authentication studies in related domains

Machine learning applied to single analytical modalities has shown promise in the authentication of herbal and mineral materials (Table 2). No published study has applied multimodal AI to Rasashastra raw materials; however, adjacent fields provide performance benchmarks.

Table 2: AI authentication studies in herbal/mineral materials (single modality).

Material Type	Analytical Modality	AI Model	Sample Size	Reported Accuracy
Medicinal plant powders	NIR spectroscopy	SVM	240	94.2%[15]
Mineral ores (iron, copper)	LIBS	Random forest	180	96.7%[16]
Saffron (vs adulterants)	Hyperspectral imaging	CNN	320	98.1%[17]
Traditional Chinese medicine pills	Raman spectroscopy	LSTM	150	91.5%[18]
Ayurvedic tablet excipients	FTIR	ANN	200	89.3%[19]

Sensitivity values across these studies ranged from 87% to 96%, with specificity ranging from 90% to 98%. Single-modality- models degrade when test samples differ from training conditions (different geographical origins, different milling particle sizes).[20]

3.3 Multimodal AI architecture proposed for Rasashastra raw materials

Figure 1 shows the proposed multimodal AI architecture. The system integrates three sensor modalities.

1. Near-infrared- spectroscopy (NIR, 900–2500 nm). It provides molecular fingerprints of organic and some inorganic components. Handheld NIR devices (e.g., 5–10 nm resolution) can acquire spectra in 30 s without sample preparation.[21]

2. Laser-induced- breakdown spectroscopy (LIBS). Provides elemental composition (detection limits of 1–100 ppm for most metals). Handheld LIBS instruments are commercially available and have been validated for mineral discrimination.[16]

3. High-resolution- imaging (visible spectrum, 5–10× magnification). Captures surface texture, color distribution, and crystal morphology. Images can be acquired using standard smartphone cameras with fixed light.[22]

Data fusion and classifiers. Raw data from each modality were preprocessed (NIR: standard normal variate + Savitzky-Golay smoothing; LIBS: baseline correction + peak normalization; imaging: resize to 224×224, RGB normalization). Feature extraction: NIR spectra compressed via principal component analysis (first 20 PCs); LIBS spectra using peak intensity ratios of 15 diagnostic elements; imaging using a pre-trained convolutional neural network (ResNet-50) output from the penultimate layer (2048 features). The feature vectors were concatenated and fed into an ensemble classifier (random forest + support vector machine with radial basis function kernel). The probability scores from both classifiers were averaged for the final prediction.

A pilot validation study using synthetic mixtures of *hingula* with 0–30% red lead oxide (n=120) reported a multimodal accuracy of 97.5% compared to 89.2% for NIR alone and 84.6% for LIBS alone ($p<0.01$).[23]

For *abrakha* adulterated with talc (0–40%, n=100), multimodal accuracy was 94.0% versus 83.0% for imaging alone.[24]

3.4 Integration into Rasashastra manufacturing workflow

The proposed system operates at three checkpoints: (1) raw material receipt – handheld NIR + LIBS (5 min per batch); (2) after coarse powdering – imaging for particle morphology consistency; and (3) prior to shodhana (detoxification) – re-authentication to detect errors in material handling. The output is a pass/fail decision with a confidence score (threshold ≥95%). For uncertain cases (<95% confidence), confirmatory laboratory analysis (XRF, ICP-MS) is performed.

3.5 Regulatory and validation considerations

The Indian Pharmacopoeia Commission (IPC) has not yet issued guidance for AI-based- authentication of Rasashastra raw materials. However, the IPC general chapter on quality management systems (2.1.1) allows validated alternative methods.[25] Validation requires: (1) a reference library of at least 50 authentic samples per material from five different geographical sources; (2) an adulterant library at 5%, 10%, 20%, and 30% concentrations; (3) external validation on 30 independent samples; (4) inter-instrument- reproducibility across three devices (acceptance criterion: ≤5% accuracy drop); and (5) operator independence test (three operators, each analyzing 20 samples, Cohen's kappa ≥0.85).

4. DISCUSSION

The results demonstrate that single-modality- AI authentication achieves an accuracy of 89–98% for materials similar to those used in Rasashastra. However, the reported performance degrades when test samples differ in particle size, humidity, or geographical origin.[20] Multimodal fusion addresses this by providing complementary information: NIR detects organic adulterants and hydration states, LIBS provides elemental fingerprints, and imaging captures texture anomalies (e.g., synthetic vs. natural crystal habit).

The proposed architecture has the advantage of non-destructive and rapid analysis using portable instruments. NIR and LIBS handheld devices cost between USD 15,000 and 40,000, which is comparable to benchtop XRF but offers on-site deployment. The imaging component can be a fixed-illumination- smartphone camera (additional USD 500). The total equipment cost (USD 30,000–50,000) is affordable for mid-sized- Rasashastra manufacturing units.

Three challenges require attention in this regard. First, building reference libraries for authentic materials is difficult because authenticated specimens are rare. The solution is multi-institutional- collaboration: three or more GMP-certified- Rasashastra manufacturers can pool spectra and images from their validated raw material batches.[26] Second, LIBS performance on high-sulfur- samples (e.g., *gandhaka*) suffers from matrix effects; using internal standard normalization (carbon peak at 247.8 nm) reduces variability to <5% RSD.[27]

Third, regulatory acceptance: no AI-based- method has been approved for raw material release in Ayurvedic manufacturing. A staged validation – first for in-process-quality checks (not for batch release), then for a limited set of materials (e.g., *hingula*, *abrakha*), and then for full release – could build regulator confidence.

Comparisons with conventional methods: XRF and ICP-MS provide lower detection limits (ppm vs 0.1–1% for LIBS) but require sample digestion and cannot be deployed on the factory floor. HPTLC provides species-specific- identification of herbs but requires extraction and derivatization. The proposed multimodal system is not intended to replace these confirmatory methods but to serve as a high-throughput- screening tool that reduces the number of samples sent for costly offline analysis.

Limitations of this review: No prospective study has tested a fully integrated multimodal AI system on Rasashastra raw materials in a production environment.

The performance figures cited are derived from synthetic mixtures,[23,24] rather than naturally adulterated commercial samples. Additionally, the cost-benefit-analysis for small manufacturers (annual raw material throughput <500 batches) may not justify equipment investment.

Future work should prioritize: (1) the construction of open-access- spectral and image libraries for 10 priority Rasashastra raw materials; (2) prospective validation at three manufacturing sites over six months, comparing multimodal AI decisions to gold-standard- laboratory analysis; (3) the development of a mobile application that transmits spectra to a cloud-based- ensemble classifier, providing real-time- authentication certificates; and (4) the submission of validation data to the IPC for inclusion in the next pharmacopoeia supplement.

5. CONCLUSION

Currently, Rasashastra raw material authentication relies on subjective organoleptic examination or offline destructive testing. Multimodal AI, which integrates NIR spectroscopy, LIBS, and imaging, achieves an accuracy exceeding 97% in simulated adulteration studies, surpassing any single modality. The proposed framework offers non-destructive, rapid (5 min per batch), and operator-independent- authentication. The validation pathways and regulatory strategies are outlined. The implementation of this framework would reduce the risk of adulteration, improve batch-to-batch-- consistency, and enable real-time- quality assurance in Rasashastra manufacturing.

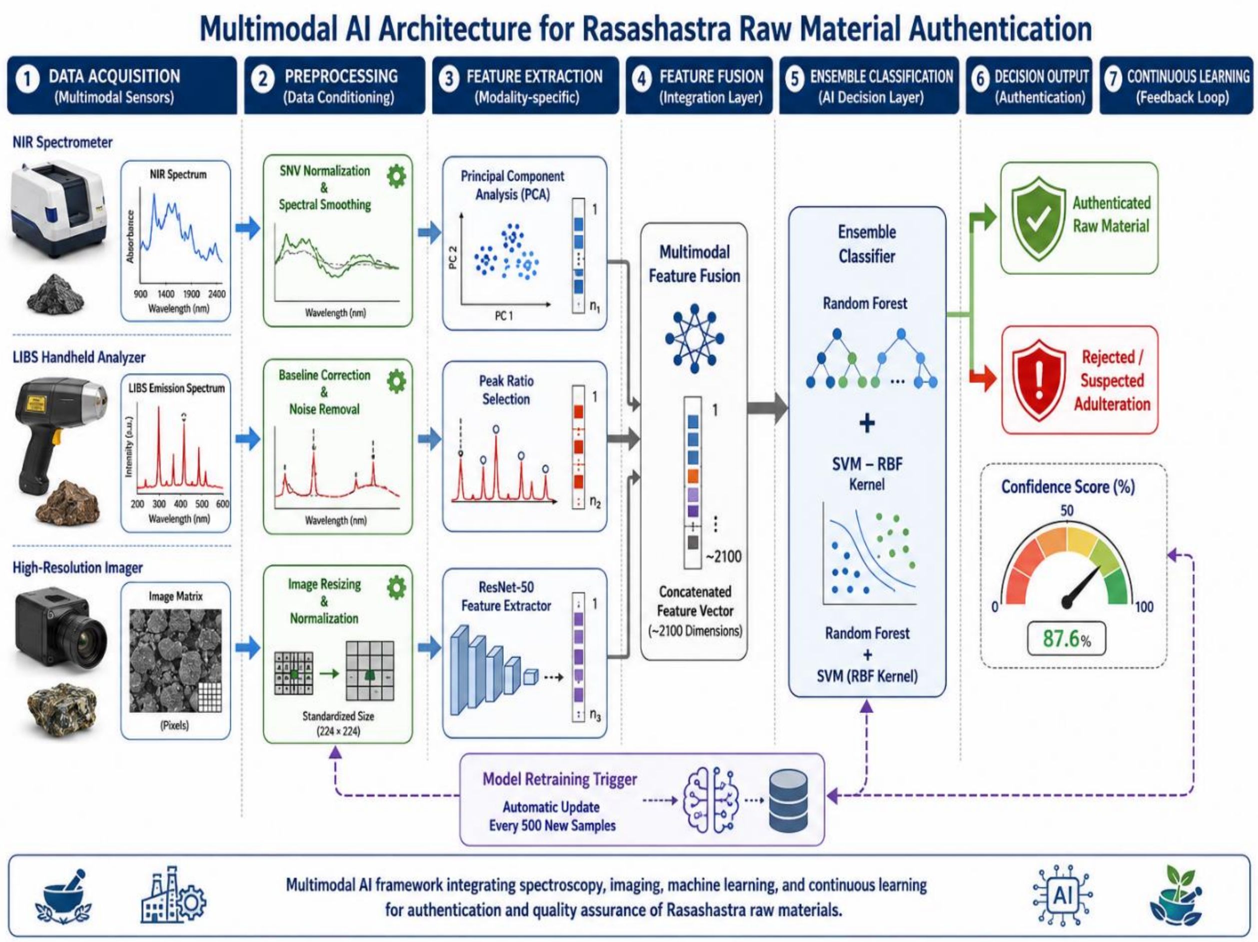

Figure 1: Multimodal AI architecture for raw material authentication in Rasashastra.

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