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Artificial Intelligence and Internet of Things-Based Food Authenticity and Adulteration Detection in Spices: A Review Paper

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Abstract. Culinary spices represent one of the most commonly adulterated agricultural commodities worldwide due to the complexity of their supply chain and the high economic value of the product. Traditional laboratory analyses (e.g., High-performance liquid chromatography, Mass spectrometry, and Wet chemical tests) are destructive, time-consuming, and insufficient for the high-throughput screening of spice powders or botanicals. This paper conducts a narrative literature review of 22 selected sources published between 2016 and 2026 that fall under seven themes: spice supply-chain risks and adulteration profiles, computer vision and deep learning approaches, portable Vis–NIR spectroscopy, electronic nose and gas sensing, multi-sensor fusion and chemometric analysis, machine learning methods for quantifying adulteration concentrations, and Edge-IoT hardware solutions. The reviewed articles demonstrate that Convolutional Neural Networks and transfer learning can reach an excellent level of precision in distinguishing between whole spices and botanical intruders, while compact Vis-NIR spectral sensors can detect food dyes and starch fillers in ground powders. SVM/Random Forest classifier-based MOS gas-sensor arrays can detect spoiled spices and vision-spectral fusion can have more accurate detection than a single modality. Nevertheless, most of the data presented in the literature is based on experiments performed on an oversimplified scenario of adulteration, and there are not enough publicly available multi-modal sensor datasets. This research presents a thematic literature review, a comparison of features in fourteen selected papers, a proposed conceptual framework, and recommendations.

Keywords: Spice Adulteration; Food Authenticity; Internet of Things; Computer Vision; Spectral Sensing; Sensor Fusion; Edge Computing

I. Introduction

Food authenticity encompasses the notion that a given food product is what the label, place of origin, composition, or commercial description claims it to be. In the case of spices, authenticity is challenging to establish since a ground product is difficult to assess visually after milling, and can be admixed with cheaper plant material, starch, spent spices, minerals, or even unauthorized dyes. The concept of authenticity also includes identity and origin statements, not merely the detection of deleterious substances, so that the appropriate test is that needed to identify the risk. Thus a camera may identify obvious differences in hue or particle size, but a chemical or elemental/isotopic analysis may be needed to detect more subtle forms of fraud. AI is valuable in that it can determine associations between a measured signal and classes of samples for which it has been trained. In the spice analysis case, input can be spectral reflectance, or images (hyperspectral, RGB), or electronic-nose signatures, or lab characterizations, and ML can be used to classify or estimate content of adulterants or be trained to identify novel classes as impostors. IoT provides a networking layer between sensors, edge devices, cloud services, and dashboards. It can

enable capture of time-stamped information on readings, device condition, storage environment, and sample identity. Blockchain is not a chemical detector – what it can contribute is that once the event has occurred and has been captured and authenticated, the entry is challenging to modify.

Recent reviews have highlighted mounting interest for the combination of AI with spectroscopy and imaging, and of IoT with traceability. Liu et al. review AI-enabled detection methodologies, alongside IoT and blockchain for food authenticity and traceability [1]. Bhat et al. discuss smart food-authentication approaches, employing combinations of AI, ML, IoT and blockchain [2]. A spice-specific review has been published by Lu et al., addressing the application of AI in the determination of origin, adulteration detection, quality assessment and sensory analysis of spices [3]. These works highlight the importance of an integrated approach, while also acknowledging the issues of data-availability, interpretation, cost and practical implementation.

1. Aim and objectives

- To review AI and sensing methods to detect adulteration and verify authenticity of spices.
- To evaluate the role of IoT for connecting test devices, recording the results and monitoring supply-chain conditions.
- To compare spectroscopy, computer vision, ML/DL and traceability approaches based on their capabilities and limitations
- To identify the research gaps that preclude their reliable, affordable, field-ready deployment
- To propose a modular AI–IoT framework for spice screening with clear validation and stepwise escalation to confirmatory testing

2. Scope

This paper focuses on dry spices and spice powders, particularly turmeric and other commonly traded spices. It aims to review the digital screening and traceability approaches rather than asserting the development or experimental validation of a new detector. The proposed framework is conceptual, and the performance values are reported only if provided in the cited study; no accuracy figure is assumed for the proposed system.

II. Review Methodology & Literature Selection Criteria

A targeted narrative review was conducted using searches of research and review literature focused on AI-based spice quality, spectroscopy for adulteration detection, smart food authentication, and IoT/blockchain traceability. The following search terms were used: “AI spice authenticity”, “machine learning spice adulteration”, “turmeric spectroscopy adulteration”, “food authenticity IoT blockchain”, “hyperspectral imaging food safety”, and “spice quality artificial intelligence”. Sources included publisher web pages and searchable/summable scholarly records from Elsevier, Taylor & Francis, MDPI and PubMed/PMC.

Inclusion criteria for a considered source were: (i) direct relevance to spices or a closely related food-authenticity context; (ii) explicit mention of the application of AI/ML to spectroscopy, imaging or sensor data; (iii) explicit discussion of IoT-enabled monitoring or digital traceability; and (iv) publication in a peer-reviewed journal or proceedings. Review articles were used to provide an overview of the research field, while specific experimental studies were used to demonstrate the pipeline from sensing to ML. The studies not including sufficient publicly available bibliographic data were excluded from consideration for quantitative performance assessment.

This is a targeted review, rather than a fully reproducible systematic review. The latter would have involved the documentation of the process from database-to-database, with removal of duplicates, screening of full-text articles, and a PRISMA flow diagram. The three assigned manuscripts mentioned in the seminar instructions were not found among the uploaded documents; these should be located and integrated prior to final submission, if the instructor has requested that one of these manuscripts be used as the primary paper.

III. Literature Review

1. AI for Spice Quality and Authenticity

Lu et al. offer a spice-centric perspective on AI applications for origin identification, adulteration detection, quality evaluation and flavour analysis [3]. The review highlights how approaches such as spectroscopy, chromatography and electronic sensors provide measurable data that ML and deep learning methods can analyze to uncover patterns that are not easily discernable by human inspection. The main limitation is that ML models need to be trained on a representative sample of the spice type, origin and instrument, before being externally validated, in order to make reliable predictions on an independent batch or origin.

2. Spectroscopy and Machine Learning for Turmeric

A 2026 study by the authors of "Machine Learning and the Use of Spectroscopy for Adulteration Detection in Turmeric Powder" investigated visible/UV and near-infrared spectral ranges using Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), a Multilayer Perceptron (MLP) and a Decision Tree [4]. The authors point out that models built using the 900–2170 nm NIR range achieved excellent independent-test classification performance, with most models scoring 100% accuracy in the described test scenario. The article evaluates approaches for selecting relevant features and identifies an SVM–League Championship Algorithm combination as a viable option for wavelength selection. These results are very interesting – but we need to remember that they are specific to the selection of samples, adulterants, concentration range, split strategy, instrument and external validation.

The main appeal of spectroscopy is that it can create a non-destructive chemical fingerprint, but a suitable spectrometer may be more expensive than a camera, and the signal may vary with the sample's water content, particle size, how densely it is packed, temperature and instrument-specific calibration. As a result, a production system would need to include reference samples, calibration verification and independent validation across suppliers and production batches.

3. AI, Detection Technologies and Traceability

Liu et al. review the integration of AI with detection methods including spectroscopy, mass spectrometry, imaging and sensors as well as IoT and blockchain-based traceability [1]. The paper presents an overview of the combination of the technologies: analytical instrumentation provides evidence about the composition, AI deals with complex patterns, IoT captures and relays the data, and blockchain can underpin the trustworthiness of the recorded supply-chain events. The review also discusses the challenges posed by heterogeneous samples, the availability of representative data, black-box models, cost and skills.

4. Smart Food Authentication

Bhat et al. review AI, ML, IoT and blockchain for food authentication and quality [2]. The effect of data on spice authenticity is highlighted: a test result is more meaningful when it can be connected to a product lot or origin claim, supplier, time of testing and chain-of-custody information. It is pointed out that traceability data cannot by themselves confirm the accuracy of the original measurement since spoofed sensor readings or incorrect entries of data at the source can be recorded anyway.

5. IoT and Blockchain Based Anti-Counterfeiting

The 2022 paper "A Food anti-counterfeiting traceability system based on Blockchain and Internet of Things" suggests using IoT to capture source data, and blockchain to maintain a distributed traceability record [5]. This addresses issues arising from centralized data storage such as data tampering and non-uniform records. For the case of spices, a similar approach could link the farm/collector, processing, packing, warehouse and retail events to a unique batch identifier. The limitation of scope applies here as traceability records can only establish a history of recorded events. Unless reliable test results are tied to the records, the product is not chemically authenticated.

6. Machine Learning with Hyperspectral Imaging

Das, Yeo and Saptoro review ML approaches used with hyperspectral imaging for food safety [6]. Hyperspectral imaging offers the combined advantage of spatial information and measurement across a range of wavelengths. It finds application where there is a need to consider the location and spectral signature of a contaminant or difference in composition. The review then enumerates methods such as PCA, PLS, SVM, ANN and CNN used across various food applications. The trade-off is that hyperspectral equipment and data processing can be computationally intensive and results from other foods cannot be assumed to be applicable to every spice.

7. Summary of Literature

Across the reviewed sources, one observes three recurring themes. First, that spectral and image based measurements can help capture variations not readily apparent to manual inspection. Second that ML performance is sensitive to the quality and representativeness of training and test data. And finally that IoT and blockchain can provide an enhanced approach towards data capture and traceability but cannot substitute for chemical validation. A useful system would need to incorporate sensing, reliable inference, addressing of uncertainties and traceable records.

IV. Comparative Analysis of Existing Studies

Technique-Level Comparison

Table 1 compares representative studies across optical spectroscopy, machine learning, IoT sensing, and blockchain traceability, outlining their analytical inputs, primary contributions, strengths, and validation constraints.

Study / approach	Input and technique	Main contribution	Strength	Limitation / caution
Liu et al. [1], 2025	Review of AI detection + IoT + blockchain	Connects analytical detection with traceability	End-to-end view across detection and supply chain	Integration and interoperability remain challenging
Bhat et al. [2], 2025	Review of smart food authentication	Examines AI, ML, IoT and blockchain	Broad view of digital authentication	Food-wide findings need spice-specific field evaluation
Lu et al. [3], 2025	Review of AI in spice quality	Maps AI for origin, adulteration, quality and flavour	Spice-specific overview	Review findings depend on the underlying studies; no single universal model
Turmeric spectroscopy study [4], 2026	UV/Vis and NIR spectra; SVM, LDA, MLP, Decision Tree	Tests ML classification and wavelength selection	Non-destructive chemical fingerprint; strong reported test results	Results are specific to its sample set and validation design; needs external replication
Food anti-counterfeiting system [5], 2022	IoT data collection and blockchain records	Traceability and anti-counterfeiting framework	Supports auditable event history	Cannot independently establish chemical authenticity

Das et al. [6], 2025	Review of ML with hyperspectral imaging	Surveys ML/DL for spectral-spatial food analysis	Rich data for complex patterns	Higher equipment, compute and deployment demands

Table 2 contrasts the core sensing, inference, and traceability technologies applied in spice authentication according to their best-suited operational roles, technical advantages, and practical limitations.

Technique	Best-suited role	Advantages	Limitations
Visual inspection / RGB camera	Initial screening of visible colour, texture, foreign particles	Low cost; easy to deploy	Cannot reliably identify hidden or chemically similar adulterants
UV–Vis / NIR spectroscopy	Composition fingerprints and adulteration classification	Rapid; potentially non-destructive	Equipment cost; calibration and sample variability
Hyperspectral imaging	Spatially resolved spectral analysis	Combines image and spectral information	Large data volume; expensive instrumentation
ML / DL	Classification, regression, anomaly detection	Learns complex patterns from data	Needs representative labels; risk of overfitting and domain shift
IoT connectivity	Timestamped sensor records, device status, environmental monitoring	Remote monitoring and dashboards	Connectivity, maintenance and cybersecurity requirements
Blockchain / tamper-evident ledger	Supply-chain event integrity and audit trail	Makes later record alteration more detectable	Cannot guarantee truth of data entered at source

V. Research Challenges & Identified Gaps

1. Limited and non-representative datasets

With sparse data it is possible to learn supplier- or instrument-specific patterns instead of the actual adulteration signal. It is important to include examples from different cultivars, seasons, regions, processing methods, particle sizes, moisture levels, brands and adulterant concentrations. Where possible, the samples should be split by batch or supplier to prevent information leakage.

2. Multi-adulterant and low-concentration detection

In practice, fraudulent samples can have a mixture of adulterants, varying proportion or even appear similar to materials used as an adulterant. A model trained to detect one type of adulteration in high concentration may not generalize to low concentrations or multiple adulterants. Future datasets should include mixtures and define the limit of detection and uncertainty.

3. Generalization and external validation
The accuracy reported for a controlled test set can be higher than that in the wild. Systems need to be externally tested on samples from different suppliers, locations, instruments and seasons. Calibration transfer and periodic re-testing should be part of the deployment plan.

4. Sensor cost, calibration and portability
While laboratory-grade spectroscopy can be highly informative, it may not be accessible to small traders or rural testing centres. Low-cost optical sensors and cameras are more accessible but may sacrifice chemical information. A two-tier system in which low-cost sensors are used for initial screening and followed by laboratory confirmation could be a viable option.

5. Explainability and trust
A simple "fake" or "authentic" label does not reveal the basis for a decision. Systems should explicitly report confidence level, potential signal location or features, calibration status and a defined "inconclusive" category. It is vital to make users aware that a screening result is not a substitute for an official certification unless the system has been validated and certified to do so.

6. IoT security and data integrity
IoT devices are prone to attacks including insecure web interfaces, compromised firmware, spoofed sensors, network outages and cloud account takeover. Device authentication, secure communication channels, access control, secure firmware updates, data encryption, audit trails and offline buffering should be taken into account. The use of blockchain cannot correct faulty data at the point of collection.

7. Standardization and cost-benefit evidence
There is a need for standard operating procedures, reference materials, model reporting standards, calibration verification and evaluation protocols. Field tests should report accuracy, false-negative and false-positive rates, latency, cost-per-sample, device availability and the volume of samples requiring laboratory confirmation.

VI. Proposed Research Directions

1. Proposed Layered Framework
A practical AI–IoT spice-authenticity system can be organized into five layers:

- Sample and identity layer: assign a unique sample/batch ID and record spice type, supplier, claimed origin, date and sample handling.
- Sensing layer: capture a standardized RGB image and, where budget permits, a UV–Vis/NIR spectral measurement. Record sensor ID, calibration status and environmental metadata.
- AI inference layer: preprocess signals, apply a validated classifier/regressor, estimate class or adulteration level, and calculate confidence or uncertainty.
- Decision layer: return “screening pass”, “suspected adulteration”, or “inconclusive”. Suspected and inconclusive samples are referred for confirmatory laboratory analysis.
- IoT and traceability layer: transmit the sample ID, timestamp, model version, result and test status to a dashboard. Store sensitive or large raw data securely; use a tamper-evident ledger for key traceability events if justified.

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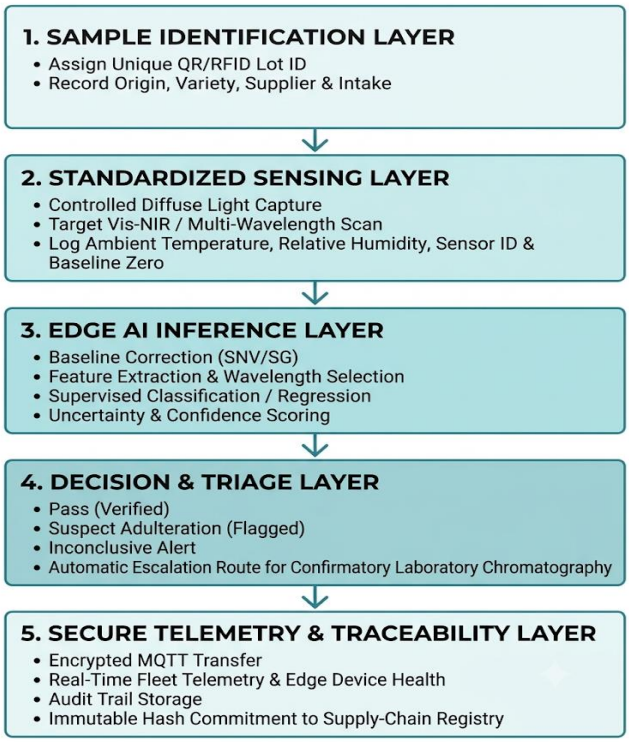


Fig. 1. Proposed workflow for spice sample analysis across five sequential stages: sample identity logging, multimodal optical sensing, uncertainty-aware AI inference, tiered screening decisions, and IoT traceability.

2. Candidate Algorithms

- For small or medium-sized labelled datasets, SVM, Random Forest and Partial Least Squares Discriminant Analysis are generally appropriate first choices for spectral data.
- Logistic regression or a decision tree might offer interpretable baselines. CNN-based models could be considered for images or high-dimensional spectral-spatial data with sufficient labelled examples.
- Choice of algorithm should be guided by controlled comparison rather than assumptions about deep learning superiority.

3. Dataset Design and Evaluation

- The dataset should comprise authenticated reference samples and adulterated samples produced or verified by a trusted laboratory procedure. Labels should specify spice variety, source, batch, adulterant type and concentration.
- Partitions should be formed to separate batches and, where possible, suppliers to assess generalization. Recommended metrics include accuracy, precision, recall, F1-score, specificity, ROC-AUC (where applicable), calibration error, inference time and per-sample operating cost.
- For safety-relevant screening, particular attention should be paid to recall for hazardous adulterants and the false-negative rate.

4. Suggested Evaluation Plan

- **Problem Definition & Confirmatory Benchmarks:** Target specific spices and high-risk adulterants with food safety toxicologists, defining secondary HPLC or GC-MS confirmatory benchmarks.
- **Curated Sample Acquisition & Ground Truth Labeling:** Secure varietal reference samples directly from verified growers; prepare controlled adulterant mixtures across realistic low-concentration intervals.

- **Sensor Rig Standardization & Environmental Testing:** Calibrate optical hardware in light-sealed fixtures, establishing baseline drift tolerances across operational temperature and humidity ranges.
- **Algorithmic Training & Independent Batch Cross-Validation:** Develop preprocessing pipelines (SNV, baseline removal) and train candidate models using leave-one-batch-out cross-validation to prevent information leakage.
- **Blind Multi-Vendor External Evaluation:** Stress-test trained models against completely unencountered market samples from multiple regions and seasons to confirm real-world performance.
- **Edge Hardware Integration & Dashboard Telemetry:** Port optimized inference models onto embedded microcontrollers (e.g., ESP32 architectures), establishing secure, encrypted cloud data pipelines.
- **Field SOP Establishment & Continuous Lifecycle Auditing:** Establish sample handling protocols, define operational triage boundaries, and configure automated alerts for sensor recalibration.

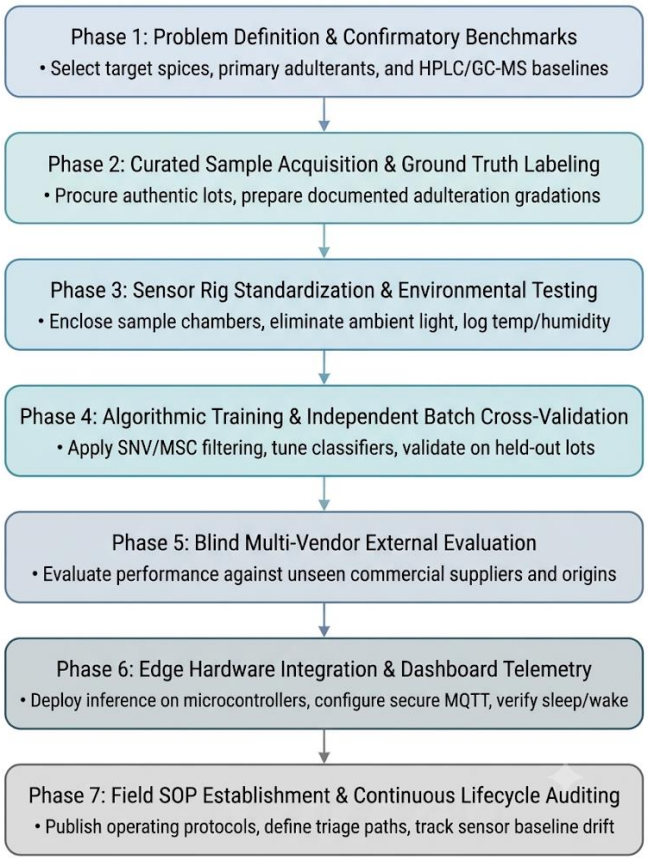


Fig. 2. seven-phase methodological lifecycle for developing, validating, and deploying an AI- and IoT-based spice adulteration detection system

VII. Conclusion & Future Scope

A combination of artificial intelligence and IoT hardware can be used to create a fast and high-throughput system for spice authentication. Vis-NIR and multispectral sensors can be used at the point of use to gather unique physiochemical data which can then be processed by machine learning models to predict quality. Simple RGB cameras can also be used as an inexpensive initial screening process to identify any obvious visual defects. IoT systems can also be used to help streamline the record

keeping process. However, whilst digital traceability systems can be used to provide security, they are unable to provide direct confirmation of the product's authenticity. Accurate authentication can be achieved through the use of representative training libraries, accurate sensor calibration and defined limits of operation. To implement these systems it is essential to have practical processes in place to ensure efficient screening. This can be achieved by using low-cost optical and gas sensors to screen samples, with clear samples automatically passed on through the process. Samples that fall within the grey area or high risk should be automatically moved onto specialist laboratory analysis. Further work should focus on creating open spectral libraries from multiple sources, detecting multiple adulterants at low concentrations, calibration transfer between devices and ensuring security of devices. By using modular design and ensuring thorough validation, these prototype systems can be developed into reliable food safety tools.

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