

Machine Learning and Gas-Sensor Arrays for Early Detection of Spoilage-Related Volatiles in Onion Storage: A Critical Review and Conceptual Early-Warning Architecture

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Abstract- Postharvest losses of stored onion bulbs (*Allium cepa* L.) arise from storage rots, sprouting, rooting and respiration-driven weight loss, and are often recognised only after visible or odorous decay has spread through a bin or shed. Because infected bulbs emit altered headspace volatiles before symptoms become obvious, continuous gas sensing combined with machine learning (ML) has been proposed as a basis for early-warning monitoring. A structured, PRISMA-informed literature search was carried out through publisher platforms, PubMed Central, Crossref metadata and institutional repositories, prioritising 2022–2026 publications and retaining foundational onion studies; every bibliographic record was verified against an authoritative source, and 29 sources were retained, including 13 onion-specific and 5 related food-spoilage primary studies. The evidence shows that onion storage pathogens, notably *Fusarium oxysporum* (basal plate rot), *Botrytis allii* (neck rot), *Burkholderia cepacia* (sour skin) and *Penicillium* spp., alter the abundance of organosulfur compounds such as methyl propyl disulfide, dipropyl disulfide and 2,2-bis(methylthio)propane, but many of these compounds are also emitted by healthy bulbs, so no single gas uniquely indicates spoilage. Metal-oxide sensor arrays, ion-mobility instruments and GC-MS-guided pattern recognition have separated inoculated from healthy bulbs with best reported accuracies of roughly 85–100 %, yet almost all onion studies used small numbers of artificially inoculated bulbs in sealed laboratory containers, random rather than grouped data splits, and no long-term drift or humidity compensation. Commercial-scale validation in onion sheds has not been reported in the peer-reviewed literature. The review contributes (i) a disease-to-volatile evidence table, (ii) a comparative analysis that separates onion-specific from analogous evidence, (iii) an eight-layer, literature-justified conceptual architecture for an edge-capable early-warning system with uncertainty handling and a gated validation loop, (iv) a leakage-resistant evaluation protocol, and (v) a prioritised agenda of research gaps that must be closed before such systems can be deployed with confidence.

Keywords— Onion Spoilage Detection; Gas Sensor Array; Electronic Nose; Machine Learning; Volatile Organic Compounds; Postharvest Storage; Internet of Things; Sensor Drift

I. INTRODUCTION

Onion is one of the most widely produced and traded vegetables, and in many producing regions the crop is harvested within a short window and then held for several months to stabilise supply and price. During that period the bulbs remain metabolically active: respiration consumes carbohydrates, water is lost through the skins, and dormancy eventually ends in sprouting and rooting, while latent or

wound-entering pathogens develop into storage rots [1]. Because bulbs are typically stored in large bins, heaps or ventilated sheds, early infections inside the mass are difficult to see, and losses are frequently recognised only after decay has become visible or smellable and has spread to neighbouring bulbs [1], [2].

Reported loss figures vary widely with region, storage structure and season, and few are based on systematic measurement. A peer-reviewed

engineering chapter describing an Indian warehouse-monitoring prototype cites storage losses of up to 15 % of production or more [3], whereas a 2026 preprint on low-cost controlled-environment storage cites 30–40 % losses for stored onions in India [4]; these figures are context-specific and should not be generalised. What the literature does agree on is the mechanism: temperature, relative humidity (RH) and ventilation strongly modulate weight loss, sprouting and rot development. In a controlled storage trial, high RH reduced mass loss but increased basal root sprouting, disease incidence and basal rotting [5], and an IoT-controlled storage study on spring onion bulbs attributed most of the variation in weight loss to temperature rather than RH or light [6].

Conventional quality assessment relies on periodic manual inspection, which is labour-intensive, samples only accessible bulbs and detects disease late. Laboratory methods such as gas chromatography–mass spectrometry (GC-MS) can resolve the volatile changes caused by infection [7], [8], but they are destructive or sample-based, slow and unsuitable for continuous on-site monitoring. This has motivated interest in low-cost gas sensors, electronic noses (enoses) and ML classifiers that could watch the headspace continuously and raise an alarm before losses escalate [2], [9]. Broader reviews of ML-supported e-noses and related artificial senses in food safety and quality describe the same trend across many commodities [10]–[12].

However, the step from a laboratory demonstration to a dependable early-warning system in a farm shed is large. Gas-sensor signals depend on temperature and humidity, drift over months, and respond to many compounds at once; spoilage labels are often defined loosely; and accuracy figures from small, artificially inoculated experiments are rarely tested on independent storage batches. A recent comprehensive review of smart sensing and IoT for onion spoilage identifies sensor specificity, calibration drift, data-processing complexity, scalability and limited validation under real storage conditions as unresolved challenges [2].

This review therefore has a deliberately critical scope. Its objectives are to: (1) review the mechanisms of onion spoilage during storage; (2) identify volatile organic compounds (VOCs) and other gases that verified studies associate with deterioration and specific storage diseases; (3) examine gas-sensing technologies suitable for storage sheds; (4) review ML methods for classifying healthy, deteriorating and spoiled bulbs or storage conditions; (5) examine integration with environmental sensing, embedded acquisition, IoT and alerting; (6) compare onion-specific and related food-spoilage systems; (7) identify research gaps; and (8) propose a literature supported conceptual architecture. The main contributions are a verified evidence base that separates onion-specific from analogous findings, an architecture that makes uncertainty and validation explicit, and an evaluation protocol designed to avoid the optimistic bias common in this literature.

II. REVIEW METHODOLOGY

1. Search strategy

The review followed a structured narrative design informed by the PRISMA 2020 reporting guideline [13]. Searches combined the terms prescribed in the review protocol, including “onion spoilage detection gas sensors”, “rotten onion machine learning”, “onion storage disease volatile organic compounds”, “onion electronic nose”, “onion quality monitoring IoT”, “machine learning gas sensor arrays”, “VOC-based food spoilage detection”, “gas sensor drift compensation”, “smart agricultural storage monitoring” and “onion rot volatile compounds”, with disease names (*Fusarium*, *Botrytis*, *Penicillium*, sour skin) and sensor names (MOS, FAIMS, GC-IMS, PEN3). The publication window prioritised 2022–2026, with earlier work retained when it was foundational to onion volatile analysis or onion gas-sensor development.

Searches were executed through a general web search engine and followed through to publisher platforms where accessible (MDPI, SpringerLink, Frontiers), PubMed Central, Crossref metadata and institutional repositories (Swedish University of Agricultural Sciences, University of Warwick, University of Georgia, Aarhus University, NIT

Rourkela). Wiley Online Library and ScienceDirect landing pages largely refused automated retrieval, so their records were verified through Crossref, DOI resolution or repository copies. Direct, logged querying of IEEE Xplore, Scopus and Web of Science was not possible from the review environment, and several publisher and metadata services intermittently refused automated requests. Consequently, database-level hit counts are not available and are not reported; authors extending this work should re-run the search strings in those databases and complete the identification stage of the flow diagram.

2. Eligibility criteria and screening

Table -1: Eligibility criteria applied during screening

Criterion	Included	Excluded
Topic	Onion (or other <i>Allium</i>) storage spoilage, storage diseases, headspace VOCs, gas sensing, e-nose, ML for VOC/sensor data, storage microclimate monitoring; closely related stored-produce spoilage sensing	Pre-harvest disease, flavour/pungency studies without spoilage relevance, non-food gas sensing
Evidence type	Peer-reviewed articles, reviews and proceedings; one clearly labelled preprint and one tradepress item used only for context	Unpublished theses; papers in venues whose peer-review process could not be verified and that reported no validation data
Verifiability	Bibliographic record confirmed against publisher, Crossref, PMC or repository	Records whose authors, venue or DOI could not be confirmed
Period	Priority 2022–2026; earlier foundational onion studies	Superseded duplicates

Each record was first screened by title and source, then assessed at abstract or full-text level. Where only metadata or an abstract was accessible, this is stated in the comparative tables and the verification log (Supplementary S1), and the corresponding claims in the text are limited accordingly.

3. Study selection

The established counts are shown in Fig. 1. Twelve records were excluded at title/source screening (eight IoT storage-monitoring papers, mostly onion-specific, in venues whose peer-review procedures could not be verified; one onion cold-storage record of unknown venue; two out-of-scope records; and one nonscholarly project page). Five relevant reports could not be retrieved or verified (for example, a 2024 onion postharvest review whose landing page was unavailable, and a 2025 book chapter whose record could not be opened). Thirty-one records were assessed at abstract or full-text level; two unpublished theses were excluded, leaving 29 retained sources: 18 primary studies (13 onion-specific, 5 other foods), 7 reviews, 3 methodological or sensor studies and 1 grey-literature item. Six standard references (reporting guideline, algorithms and sensor physics) are cited for definitions only.

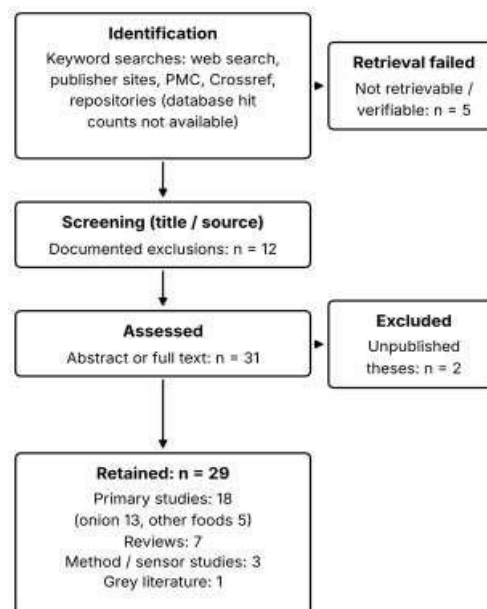


Figure 1: Study identification and selection in this review cycle. Only counts that were actually established are shown; database-level identification counts were not obtainable.

III. ONION SPOILAGE MECHANISMS AND GAS SIGNATURES

1. Deterioration mechanisms

Losses in stored onions combine physiological and pathological processes. Respiration and transpiration cause continuous loss of dry matter and water; the end of dormancy leads to sprouting and rooting; and storage diseases convert sound bulbs into unmarketable ones [1]. Storage conditions couple these processes: in experimental storage, high RH lowered mass loss but raised root sprouting, disease incidence and basal rot, whereas low RH suppressed root sprouting but increased mass loss [5]. Storage history before monitoring also matters; in the same study, differences in pre-storage holding temperature between farms confounded comparisons of conventional and organic onions [5]. These interactions mean that any gas-based monitor operates in an environment whose temperature, humidity and ventilation simultaneously change the biology and the sensor response.

2. Storage diseases and their headspace volatiles

Onion bulbs are rich in organosulfur flavour precursors, so their headspace is dominated by sulfides, disulfides and related compounds even when healthy. The central question for sensing is therefore not whether sulfur volatiles are present, but whether their quantity, ratios or the appearance of additional compounds change reliably with infection.

Botrytis, Fusarium and Erwinia. In an early GC-MS profiling study, bulbs inoculated with *Erwinia carotovora* ssp. *carotovora*, *Fusarium oxysporum* or *Botrytis allii* produced 253 detectable volatiles in total; only 59 occurred consistently across replicates, 25 were associated with one or more pathogens and 10 were unique to a single pathogen [7].

Inoculated bulbs had the most sulfur-containing compounds, whereas water-inoculated controls had relatively more terpenes, aromatics and aliphatics. *B. allii*-associated compounds included acetone, thirane and 1(methylthio)-(E)-1-propene [7]. The low reproducibility (59 of 253 compounds) is itself an

important finding: many volatiles are inconsistent between bulbs.

Sour skin (*Burkholderia cepacia*) and *Botrytis* neck rot. GC-MS analysis alongside a gas sensor array identified 24 major headspace volatiles across healthy, *B. allii*-inoculated and *B. cepacia*-inoculated bulbs; 16 occurred only in inoculated bulbs, and total volatile amounts were one to two orders of magnitude higher in inoculated bulbs than in healthy ones [14].

A FAIMS study on cv. Vaquero associated dimethyl disulfide, dipropyl disulfide, methyl propyl disulfide, undecane and 2-undecanone with sour-skin signals, but also noted that these compounds were linked to healthy controls [15].

Fusarium basal rot. GC-TOF-MS analysis of brown onion, red onion and shallot bulbs inoculated with *F. oxysporum* f. sp. *cepae* found ten compounds abundant in infected bulbs and scarce or absent in healthy ones; β -phellandrene, 2,2bis(methylthio)propane, 1-methylethyl 2-propenyl disulfide, dipropyl trisulfide and allyl propyl sulfide were rated the most promising markers [16]. The authors cautioned that compound identities were not all confirmed with standards, that sulfur compounds were abundant in healthy bulbs too, and that styrene probably originated from the containers [16]. An independent SPME-GC-MS study of *F. oxysporum* basal plate rot identified nine indicator compounds by multilevel pattern analysis, including methyl propyl disulfide, dimethyl disulfide, 2,2bis(methylthio)propane, 1-octen-3-ol and methyl 1propenyl disulfide; seven were found only in infected bulbs. *Penicillium* rot. For *Penicillium polonicum*, indicator compounds such as 2,4-dimethylthiophene and 2hexyl-5-methyl-3(2H)-furanone increased in infected bulbs, but their presence was inconsistent across samples, and accelerated sprouting in infected bulbs may have altered the profiles [8]. *Penicillium* rot therefore appears harder to detect volatilometrically than *Fusarium* basal plate rot on current evidence.

Table -2: Verified associations between onion storage diseases and headspace volatiles

Disease or condition	Reported volatile compounds or gases	Detection method	Main findings	Ref.
Botrytis neck rot (<i>B. allii</i>)	Acetone, thiirane, 1-(methylthio)-(E)-1propene, propyl carbamate and others	Headspace GC/MS	Pathogen-inoculated bulbs richest in sulfur compounds; only 59 of 253 volatiles reproducible across replicates	[7]
Fusarium rot (<i>F. oxysporum</i>) and bacterial soft rot (<i>E. carotovora</i>)	Pathogen-specific compounds reported (e.g., 3-bromofuran for <i>Erwinia</i>)	Headspace GC/MS	25 compounds pathogen-associated; 10 unique to one pathogen	[7]
Sour skin (<i>B. cepacia</i>) and Botrytis neck rot	24 major volatiles; 16 only in inoculated bulbs (individual names not captured in verified text)	GC-MS + gas sensor array	Total volatiles 10–100× higher in inoculated bulbs; sensor responses to the two diseases similar	[14]
Sour skin (<i>B. cepacia</i>)	Dimethyl disulfide, dipropyl disulfide, methyl propyl disulfide, undecane, 2undecanone	Portable FAIMS	Detected at 3 days after inoculation at room temperature, 16 days at 4 °C; compounds also linked to healthy controls	[15]
Fusarium basal rot (<i>F. oxysporum</i> f. sp. <i>cepae</i>)	β-Phellandrene, 2,2bis(methylthio)propane, 1-methylethyl 2-propenyl disulfide, dipropyl trisulfide, allyl propyl sulfide (priority markers)	GC-IMS + GC-TOF-MS	Infected bulbs distinguished from 1 day after incubation; identities not all confirmed with standards	[16]
Fusarium basal plate rot (<i>F. oxysporum</i>)	Methyl propyl disulfide, 1(methylthio)propane, dimethyl disulfide, 2,2-bis(methylthio)propane, styrene, 1-octen-3-ol, methyl 1propenyl disulfide and others	SPME-GC-MS, multilevel pattern analysis	Nine indicators; seven only in infected bulbs; clear PCA separation from controls	[8]
Penicillium rot (<i>P. polonicum</i>)	2,4-Dimethylthiophene, 2-hexyl-5methyl-3(2H)-furanone, methyl 1propenyl disulfide, 1-ethoxy-2propanol, 2-methyl-5-pentanolide	SPME-GC-MS	Indicators inconsistent between samples; sprouting may confound profiles	[8]
Storage microclimate (high vs. low RH)	Not measured (temperature and RH only)	Wireless and logged T/RH sensors	High RH increased disease incidence and basal rotting; sensors disagreed by position	[5]

3. Implications for gas sensing

Three implications follow from Table -2. First, the most consistent signals are shifts in organosulfur compounds and in total volatile load, rather than

unique ‘spoilage gases’. Compounds such as methyl propyl disulfide appear as indicators in more than one study [8], [15], but they are also part of the normal onion headspace. Second, the marker sets

differ between pathogens, analytical platforms and laboratories, and some markers (styrene, for example) can originate from equipment [16]. Third, these studies were conducted on individually enclosed or small groups of inoculated bulbs at fixed temperatures, so the concentrations reaching a sensor in a ventilated shed, diluted by large volumes of air and by healthy bulbs, are unknown.

It is therefore essential to distinguish two kinds of measurement. Detecting an individual chemical requires a selective, calibrated method, typically GCMS or a compound-specific sensor. Low-cost metaloxide semiconductor (MOS) devices, including the widely used MQ-series modules, are broadly crosssensitive: a single MOS output responds to many reducing gases and to humidity, so it cannot identify or quantify a particular disulfide. What an array of such sensors can do is produce a response pattern that an ML model may learn to associate with a labelled condition. That association is only as valid as the labels small groups of inoculated bulbs at fixed temperatures, so the concentrations reaching a

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Table -3: Gas-sensing technologies relevant to onion storage monitoring

Technology	Principle	Strengths	Limitations	Storage-shed suitability	Evidence
MOS (chemiresistive) sensors and arrays	Resistance of a heated metal-oxide film changes on gas adsorption	Low cost, high sensitivity to many reducing VOCs, simple electronics, suits arrays	Poor selectivity, strong T/RH dependence, heater power, baseline drift, poisoning	Good for patternbased screening if compensated and recalibrated	[9], [17]–[19]
Electrochemical sensors	Electrode reaction current proportional to target gas	Higher selectivity for specific gases, low power	Limited target list, finite electrolyte life, crossinterference	Useful as auxiliary selective channel	[12], [20]
Photoionization detector (PID)	UV ionisation of VOCs, measured as current	Broad VOC sensitivity, fast response	Non-specific total-VOC signal, lamp fouling, cost	Possible total-VOC channel; tested in potato store	[20]
Optical / NDIR sensors	Infrared absorption at gas-specific wavelengths	Selective and stable for CO ₂ and some gases	Few VOCs measurable at low cost	Candidate respiration indicator; onion validation lacking	[12], [20]

Commercial MOS e-nose (e.g., PEN3, 10 MOS)	Instrument with controlled sampling and MOS array	Standardised sampling, mature software	Cost, bench-top use	Research benchmark rather than permanent installation	[17]
FAIMS / GC-IMS	Ion mobility separation (GC pre-separation in GC-IMS)	High chemical resolution, early detection reported	Cost, complexity, humidity shifts peaks (FAIMS)	Periodic or central lab analysis	[15], [16]
GC-MS (with SPME)	Chromatographic separation and mass-spectral identification	Compound identification; reference method	Destructive or discrete sampling, slow, expensive	Reference labels and marker discovery only	[7], [8]

IV. GAS-SENSING TECHNOLOGIES

Table -3 summarises sensing options reported in the onion and stored-produce literature and in recent enose reviews. The laboratory instruments in the lower rows are reference methods and should not be treated as equivalent to the low-cost sensors in the upper rows.

1. Sensitivity, selectivity and response dynamics

MOS sensitivity depends on the oxide material, operating temperature, microstructure and the ambient atmosphere [18]. In an onion-specific array built from five Figaro (TGS 813, 822, 825, 826, 2620) and two FIS (SB-11A, SB-AQ8) sensors, responses to diseased bulbs were more than twice those to healthy bulbs, and the array discriminated four reference chemicals and two concentrations each of two onion-associated volatiles [9]. Response speed depended on the sampling flow, with most sensors responding faster at 1700 mL/min than at 850 mL/min [9]. These results establish sensitivity under controlled, pumped sampling; they do not establish selectivity for spoilage in mixed shed air.

2. Temperature, humidity and drift

Water adsorption on the oxide surface blocks reaction sites and shifts baseline resistance; across 16–30 °C and 45–75 % RH, three of four tested low-cost MOS sensors showed responses decreasing almost linearly with temperature and humidity, while one responded in the opposite direction [19]. Per-

sensor multiple linear regression on temperature and RH reduced the spread of corrected responses, although corrected values still drifted when room air changed [19]. For FAIMS, humidity shifted peak positions in the onion and potato study [15]. Long-term drift is a separate problem: a three-year, 16-sensor MOS dataset showed that drift progressively degrades classifiers trained on earlier data [21]. Drift arises from changes in sensing-layer morphology, poisoning and sensor replacement, and can be addressed through component correction, calibration standardisation with transfer samples, model updating or adaptive learning [22].

3. Cost, power and deployment

Recent prototypes in other foods use Arduino- or ESP32-class microcontrollers with MQ-series sensors and DHT22 temperature/RH modules [23]–[25], and an onion-storage preprint describes an ESP32 with DHT22 and MQ-135 [4]. Such hardware is inexpensive, but the tomato study identified limitations that are directly relevant to sheds: uncontrolled ambient conditions caused baseline drift, a 10-bit analogue-to-digital converter produced signal fluctuations, and a high pump flow diluted the sample [24]. Heated MOS sensors also draw continuous power, which matters for battery or solar operation. Commercial enoses and ion-mobility instruments offer better sampling control and chemical resolution but at a cost and complexity that suits periodic reference measurement rather than distributed installation [16], [17].

V. MACHINE LEARNING METHODS FOR SPOILAGE CLASSIFICATION

1. Workflow

A defensible ML pipeline for gas-sensor data comprises ten stages: (1) acquisition under a defined sampling protocol, including clean-air baseline periods; (2) signal cleaning, removing saturated, missing or out-of-range records; (3) baseline correction and normalisation; (4) feature extraction; (5) feature selection or dimensionality reduction; (6) model training; (7) hyperparameter tuning; (8) independent validation; (9) performance evaluation; and (10) deployment with monitoring. A common baseline correction for chemiresistive sensors is the relative response

$$\Delta R/R_0 = (R_s - R_0) / R_0 \quad (1)$$

where R_0 is the resistance in reference air and R_s the resistance during sample exposure; conductance ratios G/G_0 are equivalent [17], [26]. Typical features include steady-state or extreme response, area under the response curve and response slope; the onion array of [9] used exactly these three features per sensor. Environmental compensation can be expressed as a per-sensor regression of the form

$$R_s^* = \beta_0 + \beta_1 R_s + \beta_2 T + \beta_3 H + \beta_4 TH \quad (2)$$

with coefficients fitted in a controlled chamber [19]. All normalisation, feature-selection and compensation parameters must be estimated on training data only and then applied unchanged to validation and test data; otherwise information leaks from the test set into the model [27].

2. Exploratory analysis

Principal component analysis (PCA) is used in almost every reviewed study to visualise clustering of healthy and infected samples [8], [14], [17], [28]. PCA is unsupervised: it finds directions of maximum variance without reference to class labels, so it is not a classifier. Clear PCA separation is encouraging but does not guarantee that a classifier will generalise, and poor separation does not prove that classes are inseparable; in the tomato study PCA did not separate classes, and supervised linear discriminant

analysis (LDA) was used for reduction instead [24]. When LDA or any supervised reduction is used, it must be fitted inside the cross-validation loop.

3. Supervised classifiers

No algorithm is universally superior in this literature. In the Fusarium e-nose study, LDA and optimised kNN reached 89.6 % on a three-class problem, whereas an optimised SVM reached 87.5 %; on the two-class problem the SVM was best at 96.9 % [17]. In the GCIMS study, PLS-DA was best for two-class early detection (94.4 %) and SVM-DA for the three-class preliminary problem (89.6 %) [16]. In potato storage, an ensemble CNN with feature discretisation outperformed SVM, logistic regression, k-NN and a single CNN [26]. These rankings depend on dataset size, class definitions, features and validation procedure and should not be transferred to onion sheds without re-evaluation. Random Forest and XGBoost are attractive for tabular sensor features and for embedded deployment, but the absence of onionspecific evaluations means that their merit for this application is untested rather than established.

4. Matching the learning task to the data

The appropriate learning formulation depends on what labelled data exist. Supervised classification is appropriate when representative, independently verified labels exist for each class (for example, healthy, early infection and advanced rot) across varieties and storage conditions. Anomaly or novelty detection is better suited to the common real-world situation in which abundant data from normal storage are available but labelled spoilage events are rare; a model of normal behaviour can flag departures for inspection without claiming a diagnosis. Time-series prediction or regression suits progression questions, such as estimating time since infection, which reached R^2 of 0.88–0.94 in a laboratory GC-IMS study [16], or predicting storage time, which a conference report on small onions addressed with multiple linear regression [32]. In practice, a hybrid in which an anomaly detector screens for unfamiliar conditions and a supervised model classifies familiar ones offers a sensible starting point.

Table -4: Suitability of classifiers for onion gas-sensor data

Algorithm	Characteristics relevant to sensor data	Use in reviewed studies	Main caveat
Logistic regression	Linear, interpretable, outputs probabilities	Baseline in potato e-nose comparison [26]	Limited for non-linear patterns without engineered features
LDA	Linear projection maximising class separation; efficient with small samples	Onion sour skin and Fusarium studies [9], [14], [17]	Assumes shared covariance; unstable with many correlated features
SVM	Margin-based, kernels for nonlinear boundaries [29]; strong on small, high-dimensional data	Sour skin [28]; Fusarium [16], [17]	Requires scaling and careful kernel tuning; probabilities need calibration
k-NN	Instance-based, no training phase	Fusarium [16], [17]; apple ripening [23]	Sensitive to scaling, drift and irrelevant features
Decision tree / Random Forest	Ensemble of trees, handles nonlinearity and mixed features, gives feature importance [30]	Not used in the verified onion studies	Can overfit repeated measurements of the same bulb; importance biased by correlated sensors
Gradient boosting / XGBoost	Sequential boosted trees with regularisation [31]	Not used in the verified onion studies	Many hyperparameters; requires larger datasets and strict validation
ANN / 1D-CNN / ensembles	Learn features from raw time series	Potato rot ECNN in lab and store [26]	Data-hungry; less interpretable; needs drift-aware retraining
PLS-DA / regression	Latent-variable classification or regression of infection time	Fusarium early detection and infection-duration regression [16]	Linear; components must be fitted within validation folds

VI. REVIEW OF EXISTING RESEARCH

1. Onion-specific gas sensing and pattern recognition

Early sensor-array feasibility (2009–2015). Li et al. used a gas sensor array with an SVM to detect sour skin in sweet onions measured three to six days after inoculation [28]. PCA showed two distinct clusters, MANOVA confirmed significant differences ($P < 0.0001$), and a six-sensor subset, 81 % fewer sensors than the full array, achieved the best validation accuracy, 85 %, versus 69 % and 67 % for two alternative feature-selection schemes [28]. The finding that a reduced subset generalised better than larger ones is an early indication of overfitting

risk with many correlated sensors. A follow-up combined the array with GC-MS for Botrytis neck rot and sour skin, using 30 bulbs per phase and 10 bulbs per class in the threeclass phase; LDA classified the treatments with more than 97.8 % correct classification, although hierarchical clustering showed that the sensor responses to the two diseases were similar [14]. Konduru et al. then built a customised, microcontroller-based MOS array with a Teflon chamber, pump and valve [9]. With 16 bulbs (8 healthy, 8 inoculated with *B. cepacia*) measured three times daily for two days, 96 datasets were split randomly into 48 training and 48 validation sets, and LDA classified 89.6 % correctly, with 4.1 % false positives and 6.3 % false negatives [9]. Because measurements from the same bulbs could appear in

both subsets, this figure is best read as an optimistic proof of concept rather than an estimate of performance on new bulbs.

Ion-mobility and early detection (2018–2024). A portable FAIMS instrument detected sour-skin-related volatiles 3 days after inoculation at room temperature but 16 days after inoculation at 4 °C, with four replicates per treatment [15]. This temperature dependence is a key result for storage practice: cold storage slows both disease and volatile emission, delaying detection. Naive Bayes and LDA accuracies varied widely with sampling day [15]. Wesoly et al. used GC-IMS on brown onions, red onions and shallots and distinguished *Fusarium*-infected from healthy bulbs as early as one day after incubation, reporting 94.4 % accuracy for PLS-DA on two-class early detection and R^2 of 0.88–0.94 for regression of infection duration [16]. The authors noted the small sample size, laboratory setting and the practical difficulty of placing GC-IMS in a store [16].

Commercial MOS e-nose (2022). Labanska et al. used a PEN3 e-nose with ten MOS sensors on 20 *Fusarium*-inoculated and 20 control onions plus 10 inoculated and 10 control shallots, assembled into sets with 0–100 % infected bulbs and stored at 25 °C or 4 °C [17]. With 5-fold cross-validation, LDA and kNN achieved 89.6 % on three infection-severity classes and an optimised SVM achieved 96.9 % on healthy versus fully infected sets [17]. Importantly, samples stored at 4 °C were warmed to 25 °C before measurement, a laboratory step that removes the temperature confound present in a real store.

Volatile marker discovery (2004–2025). GC-MS studies supply the chemical basis for sensor selection but report no deployable classifiers. Prithiviraj et al. established pathogen-associated volatile profiles [7], and Kleman et al. identified indicator compounds for *Fusarium* basal plate rot and *Penicillium* rot from individually bagged bulbs at 20 °C, using PCA and multilevel pattern analysis without ML [8]. Their finding that *Penicillium* indicators were inconsistent warns against assuming that all storage diseases are equally detectable.

Storage quality and progression. A conference report on small onions (*A. ascalonicum*) screened 18 MOS sensors with fuzzy logic, retained four, and predicted storage time with multiple linear regression; the estimated discard time was 99 days by e-nose versus 97 days by conventional tests [32]. As only an abstract is available, the result is indicative.

2. Onion storage monitoring and IoT systems

IoT studies on onion storage focus mainly on environmental monitoring and control rather than verified spoilage detection. Ahmed et al. described gas sensors that trigger an alarm, display and SMS notification and upload records to a cloud platform, without reporting ML or validation data in the accessible abstract [3]. A Thai study used an ESP32, DHT22 and light sensor with a Blynk dashboard to optimise storage temperature and RH for spring onion bulbs over three months, identifying 20 °C and 65 % RH as the best tested condition; it used no gas sensors and had no confirmation run [6]. A 2026 preprint proposes an ESP32-based store with DHT22,

MQ-135 and UV-C disinfection, but its abstract reports target rather than measured loss reductions [4]. Islam et al. showed that two commercial temperature/RH sensors in the same experimental store disagreed enough to reverse the ranking of two chambers, which they attributed to sensor position [5]. This is a reminder that even ‘simple’ environmental channels need placement and calibration discipline.

Trade press reports a commercial Indian IoT system monitoring temperature, humidity and gases in onion stores, with about 1,000 installations and claimed detection when 2–5 % of onions in a compartment are affected at 96–97 % accuracy [33]. These figures are company statements without published independent validation and are cited only to show that commercial deployment has begun ahead of the peer-reviewed evidence.

3. Related food-spoilage studies

Potato storage is the closest analogue, because tubers are stored in bulk for months and suffer bacterial and fungal rots. Rutolo et al. combined

MOS, electrochemical, photoionisation and non-dispersive infrared sensors and, after laboratory optimisation, tested the array in a commercial research potato store, where several sensors detected and tracked early soft rot [20]. Lin et al. tested a 12-MOS portable e-nose on 300 potato samples in a laboratory and in an actual storage facility; accuracy fell from 94.70 % in the laboratory to 90.76 % in storage because ambient gases from other produce and fittings increased class overlap, and long-term drift was not corrected [26]. This laboratory-to-store drop is the most direct quantitative evidence of the generalisation gap expected for onions.

Low-cost MQ-series prototypes for fruit illustrate both promise and recurring methodological weaknesses. An apple ripening study used four MQ sensors and kNN but derived its class labels from unsupervised Kmeans clustering rather than reference measurements and tested on only nine independent samples [23]. A tomato shelf-life study fused 12 MOS sensors with colour and weight data, but its authors acknowledged uncontrolled ambient conditions and dimensionality reduction applied before the train/test split, which may inflate the regression results [24]. A fruit prototype using two MQ sensors reported 99.96 % accuracy with a linear SVM without stating its sample size [25]. These examples show why high reported accuracies in low-cost systems cannot be taken at face value. Broader reviews of signature VOCs and e-nose technology reach consistent conclusions: environmental interference, lack of standardised protocols, limited real-world validation and drift remain the main barriers [12], [34].

4. Thematic synthesis

Across the literature, four patterns emerge. (i) Feasibility is established, deployment is not. Every onion classification study used artificially inoculated bulbs in sealed containers, typically 4–20 bulbs per class [9], [15]–[17]. (ii) Detection time depends on temperature. Cold storage delayed detectable volatile changes from 3 to 16 days after inoculation [15], and e-nose studies warmed cold-stored samples before measuring [17]. (iii) Validation is rarely independent. Random splits of repeated measurements [9], k-fold cross-validation within one experiment [17] and preprocessing before splitting [24] dominate; independent test sets from different batches or seasons are essentially absent. (iv) IoT and ML are developing separately. IoT onion-storage studies emphasise connectivity and environmental control [3], [6], whereas ML studies use bench-top instruments [16], [17]; very few works integrate verified spoilage classification into a deployable, connected system, a gap also highlighted in the 2026 onion review [2].

VII. COMPARATIVE LITERATURE ANALYSIS

Tables -5 and -6 summarise the primary studies. Reported performance values are reproduced as published and are not directly comparable because datasets, class definitions, inoculation methods and validation procedures differ. 'NR' denotes information not reported in, or not verifiable from, the accessible source.

Table -5: Comparative analysis of onion-specific primary studies

No.	Authors, year	Objective	Product / disease	Sensor technology	Dataset / samples	Methodology	Reported performance	Limitations	Research opportunity
1	Prithiviraj et al., 2004 [7]	Profile volatiles to discriminate storage pathogens	Onion; <i>Erwinia</i> , <i>F. oxysporum</i> , <i>B. allii</i>	Headspace GC/MS	NR (replicated inoculations); abstract only	Compound occurrence analysis	59 of 253 volatiles reproducible; 25 pathogen-associated	Small, lab inoculation; no classifier	Confirm markers under storage conditions
2	Li et al., 2009 [28]	Detect sour skin with sensor array	Sweet onion; sour skin (<i>B. cepacia</i>)	Gas sensor array	NR in verified text; 3–6 days postinoculation	PCA, MANOVA,	85 % validation (6-sensor subset)	Single disease and variety	Sensor subset selection for

		+ SVM				feature selection, SVM			low-cost arrays
3	Li et al., 2011 [14]	Detect neck rot and sour skin; identify VOCs	Onion; <i>B. allii</i> , <i>B. cepacia</i>	Gas sensor array + GCMS	30 bulbs per phase; 10 per class	PCA, HCA, LDA	>97.8 % (3 classes)	Small n; diseases poorly separated by sensors	Disease-specific vs. generic alarms
4	Konduru et al., 2015 [9]	Develop lowcost MOS array for onion quality	Onion; sour skin	7 MOS (Figaro, FIS), PIC MCU	16 bulbs; 96 datasets	MANOVA, PCA, LDA, random 48/48 split	89.6 % (FP 4.1 %, FN 6.3 %)	Bulb-level leakage possible; lab only	Grouped validation; T/RH compensation
5	Islam et al., 2017 [5]	Evaluate microclimate tools in onion storage	Onion; storage quality	Wireless and logged T/RH	2–3 batches per type	ANOVA, PCA	High RH raised rot and rooting	No gas sensing; sensor disagreement	Sensor placement and calibration protocols
6	Sinha et al., 2018 [15]	Detect storage infection with FAIMS	Onion cv. Vaquero; sour skin	Portable FAIMS	4 replicates per treatment	PCA, Naive Bayes, LDA, 10fold CV	Detection 3 DAI (25 °C), 16 DAI (4 °C); accuracy varied by day	Small n; humidity shifts peaks	Cold-storage detection limits
7	Ahmed et al., 2022 [3]	IoT monitoring and alerting in warehouse	Onion; rotting	Gas sensors, IoT (cloud)	NR	Threshold alarm, SMS	NR	No ML or validation reported in abstract	Validated spoilage labels
8	Labanska et al., 2022 [17]	Detect Fusarium basal rot with e-nose	Onion, shallot; <i>F. oxysporum</i> f. sp. <i>cepae</i>	PEN3 (10 MOS)	40 onions, 20 shallots	PCA, LDA, SVM, k-NN, 5-fold CV	89.6 % (3class); 96.9 % (2-class)	Lab; cold samples warmed before measuring	In-store trials at storage temperature
9	Dwivedi, 2022 [32]	Non-destructive storagequality assessment	Small onion (<i>A. ascalonicum</i>)	MOS e-nose (18 screened, 4 used)	NR	Fuzzy logic, MLR	Discard time 99 d vs. 97 d (conventional)	Conference abstract only	Shelf-life prediction models
10	Wesoly et al., 2024 [16]	Early detection and VOC markers	Brown/red onion, shallot; Fusarium	GC-IMS, GC-TOF-MS	Up to 40 onions + 20 shallots per experiment	PCA, LDA, SVM-DA, k-NN, PLS-DA, PLS	94.4 % early 2class; R ² 0.88– 0.94	Small n; lab; marker identities partly unconfirmed	Translate markers to low-cost sensors
11	Kleman et al., 2025 [8]	Identify indicator VOCs	Onion; Fusarium, <i>P. polonicum</i>	SPME-GC-MS	8 infected + 6 control (Fusarium); 4 + 4 (Penicillium)	PCA, multilevel pattern analysis	9 Fusarium and 5 Penicillium indicators	No ML; single bulbs in bags at 20 °C	Sensor arrays tuned to organosulfur markers

12	Kaewchaloont et al., 2025 [6]	IoT environmental control to cut weight loss	Spring onion bulbs	ESP32, DHT22, BH1750, Blynk	~1 kg per run; L9 design, triplicate	Grey-Taguchi, ANOVA	Best: 20 °C, 65 % RH	No gas sensing; no confirmation run	Couple control with spoilage sensing
No.	Authors, year	Objective	Product / disease	Sensor technology	Dataset / samples	Methodology	Reported performance	Limitations	Research opportunity
13	Kumar & Singh, 2026 (preprint) [4]	Low-cost controlled storage with UV-C	Onion	ESP32, DHT22, MQ135	NR	Automated control	NR (targets only)	Not peer reviewed; no trial data in abstract	Field validation

Table -6: Comparative analysis of related food-spoilage primary studies

No.	Authors, year	Objective	Product / disease	Sensor technology	Dataset / samples	Methodology	Reported performance	Limitations	Relevance to onion storage
14	Rutolo et al., 2018 [20]	Detect potato soft rot in store	Potato; <i>Pectobacterium carotovorum</i>	MOS, electrochemical, PID, NDIR	NR (abstract only)	Lab optimisation then commercial research store	Early detection reported qualitatively	Metrics not in abstract	Bulk store; multitechnology array
15	Thakur & Khan, 2023 [25]	Low-cost fruit spoilage prototype	Fruit (apple/banana)	MQ3, MQ7, Arduino	NR	PCA, linear SVM	99.96 %	Sample size unstated; internal inconsistencies	Illustrates reporting pitfalls
16	Lin et al., 2024 [26]	Identify rotten potatoes in storage	Potato; natural rot	12 MOS portable enose	300 samples (10 kg lots)	Feature discretisation, ensemble CNN; SVM, LR, k-NN baselines	94.70 % lab; 90.76 % storage	No drift correction; one variety	Lab-to-store performance gap
17	Trebar et al., 2024 [23]	Classify apple ripening stages	Apple	MQ3, MQ135, MQ136, MQ138; ESP32; DHT22	4 experiments; 9 independent test samples	PCA, K-means labels, k-NN	>75 %; 100 % on some test sets	Labels from clustering, not reference	Need for independent reference labels
18	Senge et al., 2025 [24]	Predict tomato shelf life by data fusion	Tomato	12 MOS incl. MQ135/136/137/MQ3; DHT22	52 samples	LDA, SVC, k-NN, SVR, 5-fold CV	Accuracy 0.867 (scenario); R ² 0.867	Uncontrolled ambient; reduction before split	Fusion of gas and environmental data

Proposed Conceptual System Architecture

Failure modes identified in Sections 3–7. Solid arrows indicate operational data flow; dashed arrows indicate

Fig. 2 presents a proposed conceptual architecture; the offline, gated model-development loop and it has not been implemented or experimentally validated. It is derived from the requirements and optional telemetry.

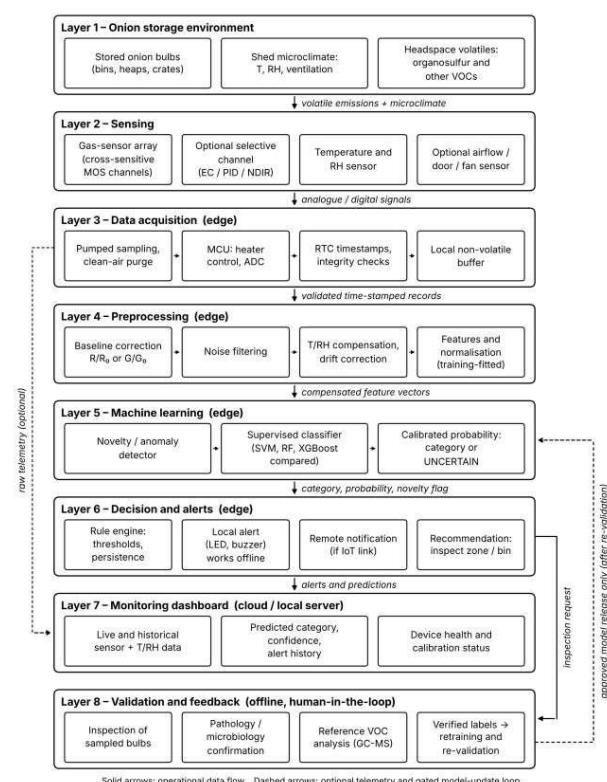


Figure 2: Proposed conceptual eight-layer architecture for ML-based early warning of onion spoilage in storage (conceptual, not experimentally validated). Solid arrows: operational flow from sensing to classification and alerts; dashed arrows: optional telemetry and the gated retraining loop, which releases a model to Layer 5 only after independent revalidation.

Layer 1 – Onion storage environment

The monitored system comprises stored bulbs, the shed microclimate (temperature, RH, ventilation) and headspace volatiles. Volatile emission depends on disease type and storage temperature [8], [15], and

the microclimate also affects disease development directly [5].

Layer 2 – Sensing

A cross-sensitive gas-sensor array, typically MOS channels of differing selectivity, provides the response pattern [9], [17]. An optional selective channel (electrochemical, PID or NDIR) adds information that MOS arrays lack, following the multitechnology design tested in potato storage [20]. Temperature and RH are mandatory for compensation [19]; airflow, door or fan-state sensors are optional but useful for explaining transient signals. The specific gas-sensor models are deliberately not fixed here, because no study has yet shown which sensors respond selectively to onion organosulfur markers at shed-level concentrations.

Layer 3 – Data acquisition

Pumped sampling with periodic clean-air purge establishes R_0 and improves response dynamics [9], [17]. A microcontroller controls sensor heaters and the pump, conditions signals and digitises them with adequate ADC resolution (the 10-bit limitation reported in [24] argues for 12-bit or better, or an external ADC). Records are timestamped from a real-time clock, as in [9], checked for range, missing values and integrity, and buffered locally so that connectivity loss does not cause data loss.

Layer 4 – Preprocessing. Baseline

correction (Eq. 1), filtering, temperature/RH compensation (Eq. 2) and drift correction, using reference or transfer samples where available [22], precede extraction of response features and normalisation with parameters frozen from training data [27].

Layer 5 – Machine learning

A novelty detector first checks whether the current feature vector resembles the training distribution. If it does, a supervised classifier assigns a validated category; SVM, Random Forest and XGBoost are listed as candidates to be compared rather than as a pre-selected solution [29]– [31]. The output is a calibrated probability; when the maximum probability falls below a threshold or the novelty

detector fires, the system reports 'uncertain' rather than forcing a label.

Layer 6 – Decision and alerts

A rule engine applies configurable thresholds with persistence (an alarm only after a condition persists for several consecutive windows) and hysteresis to limit false alarms. Local LED, buzzer or display alerts operate without internet; remote notifications are sent when an IoT link exists, as in existing onion-store prototypes [3]. Every alert recommends manual inspection of the relevant zone rather than asserting spoilage.

Layer 7 – Monitoring dashboard

A cloud or local server displays live and historical sensor and environmental data, predicted category and confidence, alert history, and device health and calibration status, extending the environmental dashboards already used in onion storage IoT [6].

Layer 8 – Validation and feedback

Inspection of sampled bulbs, pathological or microbiological confirmation and periodic reference VOC analysis by GC-MS [8], [16] generate verified, versioned labels. These labels feed offline retraining, but a new model is released to Layer 5 only after independent revalidation on data from batches not used in training. This gate prevents unverified feedback from degrading the model.

9. Architecture Design Rationale

Sensor array versus single sensor. A single broadly responsive sensor produces one number that rises with many gases, temperature and humidity, so it cannot distinguish a rot event from a change in weather or ventilation. Arrays of sensors with differing selectivity produce patterns that classifiers can separate, as all onion e-nose studies have shown [9], [17], [28]. The finding that a well-chosen subset can outperform a larger array [28] also argues for selecting sensors by validation rather than adding as many as possible.

Environmental effects and compensation

Because MOS response changes with temperature and humidity [18], [19], and because shed conditions vary daily and seasonally, uncompensated readings

will create false trends. Compensation models must be fitted per sensor and checked periodically, and drift must be corrected or the model updated using transfer samples [21], [22].

Edge versus cloud

Acquisition, preprocessing, inference and local alarms (Layers 3–6) should run at the edge so that the store remains protected when connectivity fails, which is common in rural areas. Computationally heavier tasks, such as long-term storage, dashboards, cross-site analytics and retraining, belong in the cloud or on a local server. Lightweight models (linear models, small tree ensembles) are easier to run on microcontrollers than deep networks.

Data transmission and storage

When IoT is used, compact summaries (features, predictions, health flags) can be sent at regular intervals, and raw data uploaded opportunistically from the local buffer. Records should carry device identifiers, firmware and model versions and calibration dates so that results can be traced.

Thresholds and confidence

Alert thresholds should be set from validation data to achieve an acceptable balance between missed spoilage and false alarms, and should be adjustable per store. Probabilities should be calibrated, and low-confidence or out-of-distribution outputs should be reported as uncertain and prompt inspection.

Reference measurements for labels

Sensor arrays measure patterns, not causes. Reliable training labels require independent evidence: visual and tactile inspection, pathogen confirmation and, for marker validation, GC-MS. The divergent marker sets across studies [7], [8], [16] show that labels based only on sensor thresholds would be circular.

Model Evaluation and Validation Framework

Because no experimental data are reported here, this section is a proposed evaluation protocol for future prototypes; no metric values are claimed.

Table -7: Proposed evaluation metrics and their purpose

Metric	Definition / use	Why it matters for onion storage
Accuracy	$(TP+TN)/(TP+TN+FP+FN)$	Misleading under class imbalance; report only with class-wise metrics
Precision	$TP/(TP+FP)$	Share of alarms that correspond to real spoilage
Recall (sensitivity)	$TP/(TP+FN)$	Share of spoilage events detected; primary safety metric
Specificity	$TN/(TN+FP)$	Ability to stay silent during normal storage
F1-score	Harmonic mean of precision and recall	Single summary under imbalance
Confusion matrix	Counts per true/predicted class	Shows which stages or diseases are confused
ROC-AUC / PRAUC	Threshold independent ranking quality	PR-AUC preferred when spoilage is rare
False alarm rate	False alarms per store per unit time	Determines operator trust and workload

Missed-spoilage rate	$FN/(TP+FN)$, per event	Directly linked to economic loss
Detection latency	Time from verified onset to first alert	Core value of early warning
Inference time / energy	Per prediction on target hardware	Feasibility of edge deployment
Calibration stability	Change in baseline and performance over time	Indicates need for recalibration or retraining
Cross-batch / cross-season generalisation	Performance on unseen batches, sheds, seasons	The decisive test of deployability

Class imbalance. In a real store, spoilage samples are rare. Training should use class weighting or resampling inside training folds only, and evaluation should emphasise recall, precision and PR-AUC rather than accuracy.

Data leakage and grouped splitting. Leakage, in which information from the test set influences training, is a pervasive source of over-optimistic ML results [27]. In onion studies, repeated measurements of the same bulb or set [9], [17] are strongly correlated; random splitting of measurements therefore places near-duplicates in both training and test sets. Splits should be grouped by bulb, sample set, storage batch or shed, and preprocessing should be fitted within training folds. Where feasible, the final test should use an entirely independent storage batch, shed or season, following the logic of the laboratory versus-store comparison in [26].

Temporal validation. Because drift accumulates over time [21], models should also be tested forward in time (train on earlier months, test on later months) to measure calibration stability and to set recalibration intervals.

Research Gaps and Challenges

Table -8: Validated research gaps and corresponding future directions

Gap	Supporting evidence	Why unresolved	Future direction	Horizon
Limited field validation in real onion sheds	All onion classifiers used lab containers [9], [16], [17]; 2026 review notes lack of real-storage validation [2]	Long trials are costly; spoilage events in stores are unpredictable	Multi-season trials in commercial sheds with verified labels	Near-term
Spoilage signal vs. environmental interference	T/RH effects on MOS [19]; ambient gases reduced potato accuracy in store [26]	Compensation models tested over narrow ranges	Compensation across full shed ranges; fusion of gas and environmental data	Near-term
Drift, fouling and calibration transfer	Multi-year drift degrades classifiers [21]; transfer methods reviewed [22]; drift uncorrected in potato store study [26]	No onion-specific longterm data	Transfer-sample protocols, driftaware retraining schedules	Near-term
Narrow datasets	One variety or cultivar per study [15], [26]; 4–20 bulbs per class [15], [17]	Inoculation experiments are labour-intensive	Shared, multi-variety, multidisease open datasets	Medium-term
No standard spoilage categories or reference labels	Labels from clustering [23]; inconsistent markers [7], [8]	No agreed severity scale linking pathology and VOCs	Consensus label definitions with pathology and GC-MS anchoring	Medium-term
Limited independent validation	Random or within-experiment splits [9], [17]; preprocessing before split [24]	Small datasets encourage reuse of samples	Grouped and cross-site validation as a reporting norm [27]	Near-term
Cost-selectivity-power trade-offs	Low-cost MQ prototypes vs. FAIMS/GCIMS [15], [16], [24]	Selective low-cost sensors for organosulfur markers not demonstrated	Targeted sensor materials; hybrid low-cost + periodic reference	Medium- to long-term
Limited explainability and uncertainty handling	No reviewed onion study reported calibrated uncertainty or explanations	Focus on accuracy figures	Calibrated probabilities, novelty detection, feature attribution such as SHAP [35]	Near-term
Lab VOC markers not translated to continuous sensing	Markers from GC-based methods [8], [16]; GC-IMS hard to place in-store [16]	Dilution and background in sheds unknown	Shed-level headspace concentration studies; markertargeted arrays	Medium-term
Cold-storage detection latency	Detection delayed from 3 to 16 days at 4 °C [15]; samples warmed before measuring [17]	Low emission rates at storage temperature	Sensitivity studies at storage temperature; predictive progression models	Medium-term

Table -8 lists the gaps that the reviewed evidence substantiates, why each remains unresolved, and the corresponding research direction. The candidate gaps listed in the review protocol were each tested against the literature, and all were supported.

Future Research Directions

Realistic near-term work. The most valuable immediate contribution is a carefully designed field dataset: a low-cost array with temperature/RH sensing installed in operating onion stores for at least one full storage season, with regular inspection, pathogen confirmation and periodic GC-MS reference sampling.

Such data would allow environmental compensation and drift correction to be fitted and tested over realistic ranges [19], [22], grouped and temporal validation to be applied [27], and supervised, anomaly-detection and hybrid formulations to be compared. Edge deployment of compact models with local alarms, calibrated confidence and simple explanations is technically mature enough to be built and evaluated now.

Medium-term work. Multisensor fusion of MOS, selective electrochemical or NDIR channels and environmental data, as tested in potato storage [20], should be evaluated for onions. Predictive models of spoilage progression, building on infection-duration regression [16] and storage-time prediction [32], could convert alarms into estimates of remaining safe storage time. Integration with ventilation and climate control systems [6] would let monitoring inform management decisions.

More speculative directions. Sensors with selectivity for specific organosulfur markers, transfer of models between sensor batches and stores without full recalibration, and large multi-site datasets that support deep learning remain longer-term goals whose feasibility has not yet been demonstrated for onions.

Limitations of this Review and Unresolved Questions

This review has limitations. Database-level searches of IEEE Xplore, Scopus and Web of Science could not

be logged, so relevant studies indexed only there may have been missed and identification counts are not reported. For several sources only metadata or abstracts were accessible [2], [10], [11], [20], and claims drawn from them are limited to what those records state. One preprint and one trade-press article are included for context only and are labelled as such [4], [33]. Performance figures are reported as published and were not re-analysed.

Future experimental work must answer several unresolved questions: (1) What concentrations of candidate markers reach sensors in ventilated, bulk onion stores at storage temperature? (2) Which lowcost sensors, if any, respond selectively enough to those markers? (3) How early, relative to visible symptoms, can infections be detected in practice for each major disease? (4) How often must arrays be recalibrated, and can models be transferred between units and stores? (5) What false-alarm rate will operators accept, and what detection latency is economically useful? (6) How should spoilage categories be defined so that labels are reproducible across laboratories?

VIII. CONCLUSION

Evidence from GC-MS, ion-mobility and e-nose studies shows that major onion storage diseases alter headspace volatile profiles, especially organosulfur compounds and total volatile load, and that patternrecognition models can separate inoculated from healthy bulbs under laboratory conditions. The same evidence shows why early-warning systems are not yet ready for reliable deployment. No single gas uniquely indicates spoilage; marker sets vary between diseases and studies; detection is delayed at storage temperatures; low-cost sensors are cross-sensitive and drift; and reported accuracies derive from small, artificially inoculated datasets validated without grouped or independent test sets. IoT onion-storage systems, meanwhile, have advanced connectivity and environmental control but rarely include verified spoilage classification.

The conceptual architecture proposed here addresses these weaknesses by combining a

compensated sensor array with environmental sensing, edge inference with calibrated confidence and novelty detection, local alarms that work offline, and a gated validation loop anchored in inspection, pathology and reference volatile analysis. Before such a system can be deployed with confidence, it must be validated through multi-season trials in operating onion stores, with grouped and temporal evaluation, explicit falsealarm and detection-latency targets, and documented recalibration procedures.

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REFERENCES

1. I. Kleman, "Onion storage diseases and their headspace volatiles," *Fac. Landscape Archit., Hortic. Crop Prod. Sci., Swedish Univ. Agric. Sci. (SLU), Introductory Paper No. 2023:1*, 2023, doi: 10.54612/a.602791tdo5.
2. P. Kavya, P. H. Bakane, S. R. Sakkalkar, S. R. Kalbande, S. P. Divekar, D. M. Panchbhai, and M. M. Dange, "Advancements in smart sensing and Internet of Thingsbased technologies for onion spoilage detection and postharvest quality preservation: A comprehensive review," *J. Food Process Eng.*, vol. 49, no. 7, Art. no. e70693, Jul. 2026, doi: 10.1111/jfpe.70693.
3. S. M. Ahmed, V. Reddy, R. Chandahas, and V. K. Gunjan, "Effective monitoring of onion production stored in ware house to reduce the commercial commodity wastage and improve reutilization," in *Modern Approaches in Machine Learning & Cognitive Science: A Walkthrough*, V. K. Gunjan and J. M. Zurada, Eds., *Studies in Computational Intelligence*, vol. 1027. Cham, Switzerland: Springer, 2022, pp. 343–352, doi: 10.1007/978-3-03096634-8_32.
4. S. Kumar and H. Singh, "An IoT-based controlled environment storage for prevention of spoilage of onion (*Allium cepa*) during post-harvest with UV-C disinfection," *arXiv:2601.10745 [eess.SP]*, Jan. 2026. [Preprint, not peer reviewed].
5. M. N. Islam, A. Wang, J. S. Pedersen, and M. Edelenbos, "Microclimate tools to monitor quality changes in stored onions," *Acta Hortic.*, vol. 1154, pp. 229–234, 2017, doi: 10.17660/ActaHortic.2017.1154.30.
6. A. Kaewchaloorn, K. Komane, S. Charonerat, P. Thosa, and S. Prasomthong, "IoT-based intelligent environmental control for minimizing spring onion bulb weight loss: A Grey-Taguchi optimization," *J. Eng. Technol. Access*, vol. 5, no. 1, 2025. [Online]. Available: <https://ph02.tcithaijo.org/index.php/JETA/article/download/258155/172534/985262>
7. B. Prithiviraj, A. Vikram, A. C. Kushalappa, and V. Yaylayan, "Volatile metabolite profiling for the discrimination of onion bulbs infected by *Erwinia carotovora* ssp. *carotovora*, *Fusarium oxysporum* and *Botrytis allii*," *Eur. J. Plant Pathol.*, vol. 110, no. 4, pp. 371–377, 2004, doi: 10.1023/B:EJPP.0000021058.81491.f8.
8. I. Kleman, A. K. Rosberg, O. Guzhva, M. E. Karlsson, P. G. Becher, and L. Mogren, "Headspace volatile organic compounds as indicators of *Fusarium* basal plate rot and *Penicillium* rot in stored onion bulbs," *J. Stored Prod. Res.*, vol. 114, Art. no. 102775, 2025, doi: 10.1016/j.jspr.2025.102775.
9. T. Konduru, G. C. Rains, and C. Li, "A customized metal oxide semiconductor-based gas sensor array for onion quality evaluation: System development and characterization," *Sensors*, vol. 15, no. 1, pp. 1252–1273, 2015, doi: 10.3390/s150101252.
10. M. Girmatsion, X. Tang, Q. Zhang, and P. Li, "Progress in machine learning-supported electronic nose and hyperspectral imaging technologies for food safety assessment: A review," *Food Res. Int.*, vol. 209, Art. no. 116285, 2025, doi: 10.1016/j.foodres.2025.116285.
11. L. Lu, Z. Hu, X. Hu, D. Li, and S. Tian, "Electronic tongue and electronic nose for food quality and safety," *Food Res. Int.*, vol. 162, pt. B, Art. no. 112214, Dec. 2022, doi: 10.1016/j.foodres.2022.112214.
12. T. Sanislav, G. D. Mois, S. Zeadally, S. Folea, T. C. Radoni, and E. A. Al-Suhaimi, "A comprehensive review on sensor-based electronic nose for food quality and safety," *Sensors*, vol. 25, no. 14, Art. no. 4437, 2025, doi: 10.3390/s25144437.
13. M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic

- reviews," *BMJ*, vol. 372, Art. no. n71, 2021, doi: 10.1136/bmj.n71.
14. C. Li, N. E. Schmidt, and R. Gitaitis, "Detection of onion postharvest diseases by analyses of headspace volatiles using a gas sensor array and GC-MS," *LWT—Food Sci. Technol.*, vol. 44, no. 4, pp. 1019–1025, 2011, doi: 10.1016/j.lwt.2010.11.035.
15. R. Sinha, L. R. Khot, B. K. Schroeder, and S. Sankaran, "FAIMS based volatile fingerprinting for real-time postharvest storage infections detection in stored potatoes and onions," *Postharvest Biol. Technol.*, vol. 135, pp. 83–92, 2018, doi: 10.1016/j.postharvbio.2017.09.003.
16. M. Wesoly, E. Daulton, S. Jenkins, S. van Amsterdam, J. Clarkson, and J. A. Covington, "Early detection of *Fusarium* basal rot infection in onions and shallots based on VOC profiles analysis," *J. Agric. Food Chem.*, vol. 72, no. 7, pp. 3664–3672, 2024, doi: 10.1021/acs.jafc.3c06569.
17. M. Labanska, S. van Amsterdam, S. Jenkins, J. P. Clarkson, and J. A. Covington, "Preliminary studies on detection of *Fusarium* basal rot infection in onions and shallots using electronic nose," *Sensors*, vol. 22, no. 14, Art. no. 5453, 2022, doi: 10.3390/s22145453.
18. C. Wang, L. Yin, L. Zhang, D. Xiang, and R. Gao, "Metal oxide gas sensors: Sensitivity and influencing factors," *Sensors*, vol. 10, no. 3, pp. 2088–2106, 2010, doi: 10.3390/s100302088.
19. A. N. Abdullah, K. Kamarudin, L. M. Kamarudin, A. H. Adom, S. M. Mamduh, Z. H. Mohd Juffry, and V. H. Bennetts, "Correction model for metal oxide sensor drift caused by ambient temperature and humidity," *Sensors*, vol. 22, no. 9, Art. no. 3301, 2022, doi: 10.3390/s22093301.
20. M. F. Rutolo, J. P. Clarkson, G. Harper, and J. A. Covington, "The use of gas phase detection and monitoring of potato soft rot infection in store," *Postharvest Biol. Technol.*, vol. 145, pp. 15–19, 2018, doi: 10.1016/j.postharvbio.2018.05.016.
21. A. Vergara, S. Vembu, T. Ayhan, M. A. Ryan, M. L. Homer, and R. Huerta, "Chemical gas sensor drift compensation using classifier ensembles," *Sens. Actuators B, Chem.*, vols. 166–167, pp. 320–329, 2012, doi: 10.1016/j.snb.2012.01.074.
22. A. Rudnitskaya, "Calibration update and drift correction for electronic noses and tongues," *Front. Chem.*, vol. 6, Art. no. 433, 2018, doi: 10.3389/fchem.2018.00433.
23. M. Trebar, A. Žalik, and R. Vidrih, "Assessment of 'Golden Delicious' apples using an electronic nose and machine learning to determine ripening stages," *Foods*, vol. 13, no. 16, Art. no. 2530, 2024, doi: 10.3390/foods13162530.
24. J. M. Senge, F. Kaltenecker, and C. Krupitzer, "Integrating sensor data, laboratory analysis, and computer vision in machine learning-driven e-nose systems for predicting tomato shelf life," *Chemosensors*, vol. 13, no. 7, Art. no. 255, 2025, doi: 10.3390/chemosensors13070255.
25. U. N. Thakur and A. Khan, "A prototype to prevent fruits from spoilage: An approach using sensors with machine learning," *Eng. Proc.*, vol. 58, no. 1, Art. no. 36, 2023, doi: 10.3390/ecsa-10-16005.
26. H. Lin, Z. Wei, C. Chen, Y. Huang, and J. Zhu, "Early identification of rotten potatoes using an electronic nose based on feature discretization and ensemble convolutional neural network," *Sensors*, vol. 24, no. 10, Art. no. 3105, 2024, doi: 10.3390/s24103105.
27. S. Kapoor and A. Narayanan, "Leakage and the reproducibility crisis in machine-learning-based science," *Patterns*, vol. 4, no. 9, Art. no. 100804, 2023, doi: 10.1016/j.patter.2023.100804.
28. C. Li, R. Gitaitis, B. Tollner, P. Sumner, and D. MacLean, "Onion sour skin detection using a gas sensor array and support vector machine," *Sens. Instrum. Food Qual. Saf.*, vol. 3, no. 4, pp. 193–202, 2009, doi: 10.1007/s11694-0099085-1.
29. C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995, doi: 10.1007/BF00994018.
30. L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.
31. T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, San Francisco, CA, USA, 2016, pp. 785–794, doi: 10.1145/2939672.2939785.
32. M. Dwivedi, "Development of non-destructive method for the assessment of storage quality of small onion (*A. ascalonicum*)," presented at the 21st IUFOST World Congr. Food Sci. Technol.,

- Singapore, Oct. 31–Nov. 3, 2022. [Online]. Available: <http://hdl.handle.net/2080/3812>
33. A. Fernandes, "How onion growers detect storage losses before spoilage spreads," FreshPlaza, Jul. 16, 2026. [Online]. Available: <https://www.freshplaza.com/northamerica/article/9858033/how-onion-growers-detect-storage-losses-before-spoilage-spreads/>
 34. L. Sun, J. Ma, G. Purcaro, G. Wang, J. Jin, and F. Xing, "A comprehensive review of post-harvest agricultural product deterioration signature volatile organic compounds," Food Chem.: X, vol. 29, Art. no. 102866, 2025, doi: 10.1016/j.fochx.2025.102866.
 35. S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in Proc. Adv. Neural Inf. Process. Syst., vol. 30, 2017, pp. 4765–4774.