

IoT-Based Smart Mango Ripeness and Chemical Detection: A Comprehensive Review of Ripening Physiology, Sensing and Detection Methods, IoT Architecture, Empirical Evidence, and Deployment Challenges

Chikhale Sahil Chandrakant, Prof. Abhishek Popat Bangar, Prof. Bhosale S. B., Dr. A. A. Khatr

Department of Computer Engineering,
Jaihind College of Engineering, Kuran., Maharashtra, India

Abstract — Mangoes are sold ripe, but ripeness is usually judged by colour and smell, and in many markets it is forced with industrial calcium carbide, which is illegal and leaves toxic residues. Sensing ripeness and detecting carbide with low-cost connected devices, termed here IoT-based smart mango assessment, is widely proposed as a remedy for small traders and inspectors. This paper presents a focused narrative review that synthesises five studies: a lab trial that fused an electronic nose with an acoustic firmness sensor on Harumanis mangoes, a low-cost MQ-sensor electronic nose with regression for mango sugar and hardness, an ESP32 IoT electronic nose with a dashboard tested on bananas, a visible and near-infrared spectral sensor for detecting carbide-ripened mangoes and bananas, and an electrochemical biosensor for calcium carbide. The review examines three connected themes: the physiology and chemistry that set what can be sensed, the strength of the empirical evidence, and the conditions that matter for deployment. In the first study, an electronic nose alone separated only four of six ripeness groups, while the fused system separated all six, and a neural classifier rose from 66.7% to 84.4% accuracy. The MQ-based nose predicted mango sugar content with a correlation of 0.815 and hardness with 0.847. The spectral sensor classified mango ripening method with 95% accuracy but caught only 0.67 of carbide-ripened mangoes. The biosensor reached a detection limit of 0.6 nM. No study combines ripeness sensing, carbide detection and IoT reporting on mangoes in one tested device. The review contributes a comparative table, a conceptual architecture for a connected mango ripeness and carbide screening unit, and a prioritised agenda of research gaps.

Keywords— Mango ripeness, calcium carbide, electronic nose, gas sensors, multispectral sensing, IoT, ESP32, food safety.

I. INTRODUCTION

Mango is a climacteric fruit: it keeps ripening after harvest, with a burst of ethylene release, a sharp rise in carbon dioxide and a fall in oxygen [1]. Ripeness decides price and eating quality, yet in most markets it is judged by size, shape, colour and smell, which is cheap but subjective [3]. Post-harvest losses of 20–30% are estimated for developing economies [3], and handheld fruit quality meters are costly and need training [3].

Ripening is also forced. Industrial-grade calcium carbide is widely used because it is cheap, and when it meets moisture it releases acetylene, which acts like ethylene [4]. The practice is described as illegal in [4] and as a health hazard in [5]. Carbide-grade acetylene can carry traces of phosphine and arsine, up to 95 and 3 ppm, as cited in [4]. For mangoes from Pakistan, one study cited in [4] found an arsenic cancer-risk value of 1.4×10^{-3} against an acceptable upper limit of 1.0×10^{-4} . A fruit can look ripe on the outside while being unsafe, so colour alone cannot separate good from bad.

Low-cost gas, optical and electrochemical sensors, joined to a microcontroller and a dashboard, are the usual proposal for both problems [3], [4]. In this paper, IoT-based smart mango assessment means a device that senses ripeness or ripening-agent signals, processes them locally or in the cloud, and reports the result to a trader, farmer or inspector. It differs from laboratory gas chromatography, which is accurate but slow and needs trained staff [1]. Reviewers also warn that attractive designs run ahead of field evidence, so evidence strength is a central concern here.

This paper reviews five studies: an electronic nose fused with an acoustic sensor [1], an MQ-sensor electronic nose with regression [2], an IoT electronic nose with a dashboard [3], a multispectral carbide-detection framework [4] and an electrochemical carbide biosensor [5]. Three questions guide the review. RQ1: Which physiological and chemical signals and which sensing elements underpin mango ripeness and carbide detection? RQ2: How strong is the evidence that low-cost sensing works? RQ3: What does the evidence imply for

deployment by small traders and inspectors? The paper ends with a comparative table, a conceptual architecture and a list of research gaps.

II. REVIEW METHODOLOGY

This is a narrative review of a purposively chosen set of five papers, not a systematic database search, so no claim of exhaustive coverage is made. The papers are an article in Sensors [1], an article in Smart Agricultural Technology [2], two arXiv preprints [3], [4] and an article in Analytical Methods [5].

For each paper the aim, design, scale, main findings and stated limitations were extracted and compared. All figures quoted are those reported by the original authors. The full text of [1] and [3] was read. For [2] and [5] only the published abstract was available to the reviewers, and for [4] the abstract and a third-party summary of the preprint were available because its PDF could not be machine-read. Details that those sources do not give, such as cultivar, sample size or cost, are marked “not stated” rather than guessed. Studies that these papers cite are described only as the citing paper describes them and are marked “as cited in”; they were not independently re-read.

The five papers differ in kind: two report ripeness experiments on mangoes [1], [2], one reports an IoT design with data from bananas only [3], one reports a spectral classifier for carbide-ripened mangoes and bananas [4], and one reports a laboratory biosensor [5]. None is a field trial. Conclusions about a combined, connected mango device are therefore inferences, and are labelled as such.

III. THEORETICAL FOUNDATIONS

1. Climacteric ripening and its volatile signature

Ripening changes what a mango releases and how it feels. In the Harumanis trial, GC-MS found 12 prominent headspace compounds [1]. Ethylene, the two pinenes, diethyl phthalate and a methyl ester were present from the mature stage on. Several esters appeared from the nearly ripe stage, and pentyl octanoate and one other compound appeared only at the ripe stage [1]. Texture and sugar follow. Mangoes harvested at week 7 were firmer on day 2 than those harvested at week 8, but they shrivelled faster [1]. In a second study, hardness fell from 15.4 to 12.25 kgf/cm² while soluble sugar rose from 19.7 to 24.66 °Brix over storage [2]. These shifts are what a sensor must track.

2. Signals and what they mean

Each signal answers a different question, which is why one sensor cannot serve every purpose [1]–[5].

Table 1. Signals, Meanings and Sensing Elements

Signal	What it indicates	How it was sensed	Src.
Ethylene and aroma volatiles (terpenes, esters)	Maturity and ripeness stage	Electronic nose, GC-MS	[1]
Firmness index	Softening during ripening	Acoustic tap sensor	[1]
Hardness and soluble sugar	Eating-quality ripeness	MQ gas sensors with regression	[2]
Ethanol, methane, ammonia	Ripening, then decomposition (bananas)	MQ-3, MQ-4, MQ-135	[3]
Visible versus near-infrared intensity, 410–940 nm	Carbide versus natural or ethephon ripening	Spectral triad sensor	[4]
Calcium peroxide and acetylene mixture	Carbide presence in fruit	Enzyme-modified electrode	[5]

Source: compiled by the reviewers from [1]–[5].

3. Carbide chemistry

Calcium carbide reacts with moisture to give acetylene and calcium hydroxide, and both diffuse into the fruit [5]. Carbide is unstable in water, which makes its detection hard [5]. Acetylene triggers the same ripening signal as ethylene, so, in the reviewers' view, a sensor that reads only ethylene-like ripening effects could be fooled. The spectral study reports a sharper fall in visible-light intensity for carbide-treated fruit, consistent with faster chlorophyll loss and carotenoid build-up [4]. A summary of the paper adds that near-infrared bands did not change in proportion, which the authors read as colour running ahead of internal ripening [4].

4. Reference methods and their cost

The reference method for volatiles is GC-MS. In [1] it needed at least 60 minutes of incubation and 30 minutes of needle exposure per sample, which is why the authors turned to an electronic nose [1]. Destructive tests such as Brix, pH and hardness remain the ground truth in [1] and [2], so any low-cost device is judged against slow methods.

IV. SYSTEM DESIGN ELEMENTS AND SENSING PRINCIPLES

1. Common elements

The reviewed systems share a small set of elements: a closed sampling chamber, one or more sensors, a temperature and humidity sensor, a processing step that turns raw signals into a ripeness or safety verdict, and a way to show the result [1]–[5].

2.. Elements in the laboratory electronic nose

The Harumanis study used a Cyranose 320 with 32 carbon-black conducting-polymer sensors and an acoustic firmness unit that taps the fruit and records its resonance [1]. Each mango sat in a sealed acrylic jar purged with dry nitrogen and left for 30 minutes at 26 °C. The nose then drew sample for 50 seconds and purged for 60 seconds, five times per fruit [1]. This is a controlled bench method, not a field one.

3. Elements in the low-cost MQ electronic nose

The mango study in [2] builds its nose from low-cost MQ sensors and links their readings to hardness and sugar with multiple linear regression [2]. The IoT design in [3] uses an ESP32 with MQ-3 for ethanol (25–500 ppm), MQ-4 for methane (300–10,000 ppm), MQ-135 for ammonia (10–1,000 ppm) and a DHT22 for temperature and humidity, all inside a 28.5 × 24 × 17 cm sealed container [3]. Each MQ element is tin dioxide on a ceramic base heated to 200–300 °C, and its resistance falls as target gases react on the surface [3].

4. Elements in the carbide detectors

The spectral design reads 18 wavelengths from 410 to 940 nm with an AS7265x sensor, inside a light-tight enclosure with the fruit 5 cm away, and adds temperature and humidity from an SHT40 [4]. Its features are wavelength ratios reduced by PCA, and XGBoost models give the method class, ripening percentage and shelf life [4]. The biosensor is a platinum electrode with a ceria nano-interface and the enzyme acetylcholinesterase, and carbide is sensed as inhibition of the enzyme by calcium peroxide and acetylene [5].

5. Sensing and control elements

Table 2. Sensing and Control Elements Of [3] And [4]

Element	Bhattacharjee et al. [3]	Singh et al. [4]
Controller	ESP32	ESP32
Sensing	MQ-3, MQ-4, MQ-135, DHT22	AS7265x (18 bands), SHT40

Element	Bhattacharjee et al. [3]	Singh et al. [4]
Decision logic	Gas thresholds give a weighted quality index	XGBoost classifier and two regressors
Actuation	None; display only	None; scoring only
Remote link	Google Sheet log each minute and a web dashboard in Bengali and English	Not stated in the material available
Evidence	Bananas only, 765 g, over three days at 32 °C and 97% RH	40 mangoes and 60 bananas over an 11-day window, per a summary of the preprint
Cost	About 2,200 BDT (18 USD)	Not stated

Source: [3] and [4].

6. Cautions

Several cautions recur. MQ sensors respond to more than one gas, and the authors of [3] say they cannot be certain that a resistance change comes from the named gas. These sensors are also sensitive to supply-voltage jumps and vibration, need a long settling time, and give thresholds that depend on the container design [3]. Humidity disturbs the signal too: in [1], a 45-minute incubation left water droplets in the jar and the nose readings were affected. An electronic nose alone could not tell the six ripeness groups apart [1].

Three cautions are the reviewers' own inferences. First, none of the three MQ sensors in [3] targets ethylene or acetylene, so that design cannot be said to detect carbide; that needs a different channel such as [4] or [5]. Second, because carbide-ripened fruit can show ripe colour before it is ripe inside [4], a ripeness score and a carbide flag should be reported separately, not merged. Third, the Harumanis study lists a carbide step among its ripening stages [1] but does not analyse carbide fruit as its own class, so carbide's effect on the nose is not isolated.

V. EVIDENCE OF EFFECTIVENESS

1. Fusing an electronic nose with an acoustic sensor

Harumanis mangoes from two harvest dates (week 7 and week 8) were measured on days 2, 4 and 7, giving six maturity and ripeness groups from 240 fruit [1]. The electronic nose could separate the two harvest dates, but with all six groups it failed: PCA found two groups and LDA found four [1]. Adding the

two acoustic firmness values to the 32 nose sensors, as one 34-variable input, let LDA separate all six [1].

Table 3. E-Nose and Acoustic Fusion Results [1]

Method	Groups separated (of 6)	Result
E-nose, PCA	2	Not usable for six groups
E-nose, LDA	4	Not usable for six groups
E-nose + acoustic, LDA	6	100% on training data; 479 of 480 correct in cross-validation
E-nose, LDA-CLNN	4 clusters	66.7% correct
E-nose + acoustic, LDA-CLNN	6 clusters	84.4% correct

Source: Tables 8 and 10 of [1]. The neural classifier used 120 samples (25%) for training and 360 (75%) for testing.

Sugar and acidity rose with time, and more strongly for the later harvest [1]:

Table 4. Brix and Ph by Harvest and Day [1]

Harvest	Brix, day 2 / 4 / 7	pH, day 2 / 4 / 7
Week 7 (green)	18.9 / 20.3 / 21.6	4.93 / 5.37 / 5.54
Week 8 (mature)	20.6 / 21.3 / 24.4	4.93 / 5.99 / 6.22

Source: Table 5(b) of [1], means of three repeats.

2. Low-cost MQ nose with regression

Over storage, mango hardness fell from 15.4 to 12.25 kgf/cm² and soluble sugar rose from 19.7 to 24.66 °Brix [2]. MQ sensor readings correlated positively with sugar and negatively with hardness. Multiple linear regression predicted hardness with a correlation of 0.847 and a standard error of 1.49 kgf/cm², and sugar with 0.815 and 1.696 °Brix [2]. The authors call this a rapid, non-destructive method [2]. The abstract does not give the cultivar, sample count or test design.

3. IoT electronic nose with a dashboard

Bananas weighing 765 g sat in the sealed container at 32 °C and 97% RH while the ESP32 logged each sensor every minute for more than three days [3]. All three gas readings rose over time. Ripening showed on day 1, and a rise in methane and ammonia between days 2 and 3 marked the start of decomposition [3]. The authors set ripe and decomposed thresholds from the fruit's

colour and smell and combined them into a weighted quality index [3]:

Table 5. Gas Thresholds for Bananas [3]

Gas	Ripe (ppm/kg)	Decomposed (ppm/kg)	Signal-to-noise ratio
Methane (MQ-4)	92	177	24.73
Ethanol (MQ-3)	81	108	19.64
Ammonia (MQ-135)	48	111	44.24

Source: Tables III and V of [3]. Index weights were 0.3 for methane, 0.325 for ammonia, 0.15 for ethanol, 0.125 for temperature and 0.1 for humidity.

The index dropped between days 2 and 3, when the bananas began to decompose [3]. The authors say this approach trades classification accuracy for interpretability and low computing needs [3]. Mangoes are mentioned only as a fruit type that ripens and decays slowly; none was tested.

4. Detecting calcium carbide

The spectral framework was tested on mangoes and bananas ripened naturally, with ethephon, or with carbide [4]:

Table 6. Spectral Carbide-Detection Results [4]

Fruit	Accuracy	Carbide recall	Ripeness R ²	Shelf-life RMSE (days)
Mango	95%	0.67	0.75	1.86
Banana	81%	0.74	0.87	1.30

Source: abstract of [4] for accuracy and recall; R² and RMSE from a summary of the preprint. Held-out fruit only.

The electrochemical biosensor reached a detection limit of 0.6 nM over a linear range of 1–20 nM, with recoveries of 97.89–104.82% [5]. Reference [4] also cites NIR spectroscopy as an effective approach to carbide-ripened fruit (as cited in [4]: Lakade et al., 2019; Macadaeg, 2025).

5. Quality of the evidence

No study is a field or market trial. Sample sizes are small: 240 mangoes in [1], 40 mangoes in [4], one 765 g lot of bananas in [3], and not stated for [2]. In [1] the fused-LDA text gives 98.8% cross-validated accuracy but the table counts, 479 of 480, equal 99.8%. In [3] the ripe and decomposed thresholds rest on visual judgement, and they depend on the container.

The most important caution concerns [4]. A summary of the preprint says each ripening method was applied to its own batch, with no replication, so the classifier may be separating batches rather than carbide, and the authors themselves call for independent fruit batches [4]. This should be checked against the full text. The mango hold-out was about eight fruit, so a carbide recall of 0.67 rests on very few samples. At face value it means about one carbide-ripened mango in three would pass. Finally, no study measures ripeness, carbide and connectivity on mangoes together.

VI. DEPLOYMENT: COST, POWER AND SMALL-TRADER CONSIDERATIONS

1. Cost and power

The IoT electronic nose in [3] costs about 2,200 BDT, roughly 18 USD, and its three MQ sensors draw at most about 2.85 W together by their datasheet limits, with the authors giving a combined maximum of 4 W for the full sensor set [3]. The laboratory nose in [1] is a commercial instrument whose price is not reported. Cost and power are not stated for [2], [4] or [5]. The spectral sensor is described as cheap and portable in a summary of [4], but no price is given in the material available. The biosensor in [5] needs a prepared enzyme electrode and a lab readout, so it suits confirmation, not a market stall.

2. Environment and set-up

The test conditions differ sharply. The Harumanis fruit sat in nitrogen-purged jars at 26 °C [1], which no trader can copy. The banana test ran at 32 °C and 97% RH, closer to a real market, and the authors note that gas readings depend on container design and sensor position [3]. Reading frames also matter: the spectral sensor needs a light-tight box and a fixed 5 cm distance [4], so a hand-held reading in sunlight would not match its training data. This is an inference, since [4] reports no field readings.

3. Who reads the result

For farmers and traders the output must be simple. The dashboard in [3] shows five quality bands from Excellent to Rotten in Bengali and English [3]. For Maharashtra a Marathi and Hindi version would be the equivalent step; this is the reviewers' suggestion, not a finding. For an inspector the output must be a flag with a known miss rate. With a carbide recall of 0.67 on mangoes [4], a positive flag could prompt a confirmatory test, but a negative could not clear a lot.

4. Claims that need care

The summary of [4] describes a controlled set-up, but its accuracy claim stands on one batch per ripening method, as

noted in Section 5. Reference [3] describes its thresholds as depending on container design and tests only bananas. Reference [2] gives a correlation of about 0.8 from regression, which is useful for tracking trends but not for grading a single fruit. None reports behaviour during power cuts or sensor drift over weeks.

5. Transferability

The studies span a Malaysian cultivar in the lab [1], a banana test in Bangladesh [3], and fruit of an unstated variety and site in [2] and [4]. No study tests Indian cultivars, hot dispatch yards, ripening chambers or transport vehicles, so transfer to Maharashtra markets remains untested.

VII. COMPARATIVE ANALYSIS

Table VII summarises the five reviewed studies. Findings are not directly comparable because designs, scales and outcome measures differ.

Table 7. Comparison of the Five Reviewed Studies

Study	Objective and design / sample	Main findings and limitations
Zakaria et al. (2012) [1]	Aim: classify Harumanis maturity and ripeness by fusing an electronic nose with an acoustic sensor. Design: lab experiment, 240 mangoes, six groups, days 2, 4 and 7.	Findings: nose alone separates 2 (PCA) or 4 (LDA) of 6 groups; fused LDA separates all 6; LDA-CLNN accuracy 66.7% to 84.4%. Limits: one cultivar; commercial lab instrument in purged jars; no IoT; carbide not analysed as a class; 98.8% versus 99.8% mismatch.
Rahman et al. (2024) [2]	Aim: predict mango hardness and sugar with an MQ-sensor nose. Design: storage trial with multiple linear regression; sample size not stated in the abstract.	Findings: correlation 0.847 for hardness and 0.815 for sugar. Limits: abstract only; no carbide; no IoT link stated; cultivar not stated.

Study	Objective and design / sample	Main findings and limitations
Bhattacharjee et al. (2025) [3]	Aim: low-cost IoT electronic nose with a dashboard. Design: ESP32 with MQ-3, MQ-4, MQ-135; 765 g of bananas, more than three days.	Findings: gas thresholds and a quality index that falls at days 2 to 3; cost about 18 USD. Limits: bananas only; one lot; thresholds set from visual cues; container-dependent.
Singh et al. (2026) [4]	Aim: detect carbide-ripened mangoes and bananas and estimate ripeness and shelf life. Design: AS7265x with ESP32; 40 mangoes and 60 bananas.	Findings: mango 95% accuracy, carbide recall 0.67; banana 81%, 0.74. Limits: preprint; likely one batch per ripening method; small hold-out; fixed enclosure.
Prabakaran et al. (2016) [5]	Aim: electrochemical detection of carbide in mangoes. Design: laboratory enzyme biosensor.	Findings: detection limit 0.6 nM, linear range 1–20 nM, recovery 97.89–104.82%. Limits: abstract only; lab method; field use and wireless readout not stated.

The sources agree on four points. One gas channel is not enough: the nose alone failed on six groups [1], and a second modality fixed it [1]. Cheap MQ sensors can track ripening trends [2], [3]. Carbide detection relies on different signals from ripeness, namely optical or electrochemical ones [4], [5]. The strongest numbers, 100% in [1] and 95% in [4], come from small or controlled sets. The one design with a dashboard and cloud logging [3] has no mango data, and the mango studies [1], [2] have no IoT link. That gap is the subject of the next section.

VIII. PROPOSED CONCEPTUAL ARCHITECTURE

Figure 1 gathers the design implications of the reviewed studies into a layered architecture for a connected mango ripeness and

carbide screening unit. It is a conceptual proposal derived from the literature and has not been tested experimentally.

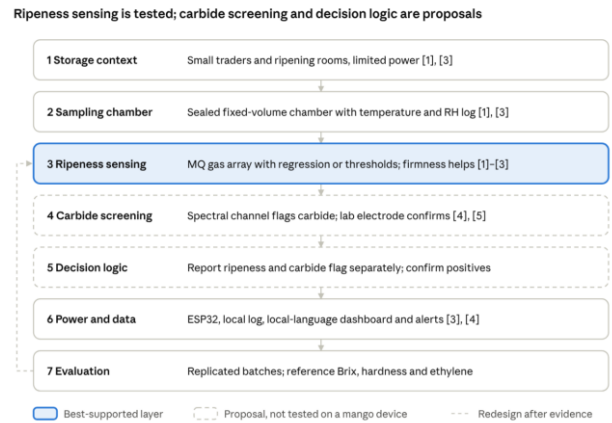


Fig. 1. Proposed conceptual architecture for a connected mango ripeness and carbide screening unit (conceptual, not experimentally validated).

Layer 1 captures the context: small traders, ripening rooms and limited power [1], [3]. Layer 2 is the sampling chamber: a sealed, fixed-volume container with temperature and humidity logging, since readings depend on the container [1], [3]. Layer 3 is the best-supported element: a low-cost gas array turned into ripeness values by regression or thresholds [2], [3], with a firmness reading added where possible because fusion helped in [1]. Layer 4 is the reviewers' proposal for carbide: a spectral channel to raise a flag [4], with the laboratory electrode in [5] as the confirming test. Layer 5 is the authors' inference: report ripeness and the carbide flag separately, and confirm every positive, because a carbide-ripened mango can look ripe [4] and the flag misses about one in three [4]. Layer 6 supplies power and data, with an ESP32 and a local-language dashboard as in [3]. Layer 7 closes the loop with replicated mango batches measured against reference Brix, hardness and ethylene, with the results fed back into layers 3 to 5.

IX. RESEARCH GAPS AND FUTURE DIRECTIONS

Gaps supported by the reviewed evidence. (i) No joint device: no study senses ripeness, detects carbide and reports over IoT on mangoes together. (ii) Little mango IoT data: the only dashboard design [3] was tested on bananas. (iii) Small, unreplicated sets: [4] appears to use one batch per ripening method and [1] one cultivar. (iv) Weak reference truth: [3] sets thresholds from colour and smell, not from chemical or

hardness tests. (v) Sensor channels not matched to the target: the MQ sensors in [3] read ethanol, methane and ammonia, not ethylene or acetylene, an inference from their datasheet targets. (vi) Narrow conditions: a Malaysian cultivar in the lab [1], a banana lot at 32 °C [3], and no Indian cultivar or market trial. (vii) Energy, drift and outage behaviour are untested. (viii) The miss rate for carbide, 0.67 recall on mangoes [4], is too low for enforcement use.

Directions requiring investigation. Priorities include a replicated trial of one mango cultivar with at least three independent batches each for natural, ethephon and carbide ripening, from at least two source lots, training on some lots and testing on others; logging an MQ gas array, a spectral sensor, an acoustic or firmness reading and temperature and humidity together, against reference hardness, Brix and ethylene over the whole ripening period; testing whether fusing gas, spectral and firmness data helps as it did in [1]; a carbide dose series that includes residue-level exposure; use of the electrochemical test [5] as a confirmatory step for flagged lots; measurement of daily energy use, sensor drift and recalibration need; and a field trial with traders using a local-language dashboard.

X. CONCLUSION

Across the five reviewed studies, low-cost sensing can track mango ripening, but no single cheap channel does the whole job. An electronic nose alone separated only four of six ripeness groups, and adding an acoustic firmness sensor separated all six [1].

MQ gas sensors predicted mango sugar and hardness with correlations near 0.8 [2], and an ESP32 nose with a dashboard tracked ripening and decay in bananas for about 18 USD [3]. Carbide detection relies on other signals: a visible and near-infrared sensor classified ripening method with 95% accuracy on mangoes but caught only 0.67 of carbide-ripened fruit [4], and a laboratory biosensor reached 0.6 nM [5].

For small traders this points to a two-part design: a gas and temperature unit for ripeness with a simple local-language display, plus a separate carbide flag from an optical channel, confirmed by a lab test before any lot is judged unsafe. Joining the two on one mango device is a proposal, not a result. A replicated, multi-batch trial that measures ripeness, carbide and connectivity together on mangoes is needed before such a unit can be recommended for markets or inspections.

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