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SPOILALERT: A COMPREHENSIVE SURVEY ON MULTISENSORY AND VISION-BASED TECHNIQUE FOR VEGETABLE AND FRUITS SPOILAGE DETECTION WITH SHELF-LIFE PREDICTION

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ABSTRACT

The global food supply chain suffers significant economic losses due to the spoilage of perishable commodities, particularly vegetables and fruits. Early and accurate detection of spoilage is critical for reducing waste, ensuring food safety, and optimizing inventory management. This survey paper presents a systematic review of modern techniques for vegetable and fruit spoilage detection using multiple sensors and camera-based imaging systems. It specifically focuses on the development of portable devices capable of real-time spoilage assessment and shelf-life display. The paper compares various sensor modalities including gas, temperature, humidity, and spectral sensors, along with computer vision and machine learning algorithms. Finally, challenges related to sensor fusion, portability, power consumption, and environmental variability are discussed, followed by future research directions.

KEYWORDS: Fruit spoilage detection, vegetable spoilage, multi sensor fusion, portable device, computer vision, shelf life prediction, IoT, food quality monitoring.

1. INTRODUCTION

Every year, roughly one-third of all the food grown around the world never gets eaten, and a big part of that loss happens simply because fruits and vegetables go bad during storage, shipping, or while sitting on store shelves [1]. This is not a small problem — it costs farmers, businesses, and consumers enormously, and it puts unnecessary pressure on land, water, and energy that went into growing that food in the first place [2]. The usual ways of catching spoilage early — someone eyeballing the produce, sniffing for bad smells, or sending samples off to a lab — are slow, inconsistent, and completely impractical when you are dealing with large quantities or need answers quickly [3]. What one person considers slightly off, another might pass as fine, and by the time lab results come back, entire batches may already be ruined [4].

This is why researchers have been putting serious effort into building smarter, portable tools that can check freshness without cutting, crushing, or damaging the produce at all [5]. The idea is to combine different types of sensors — ones that pick-up gases like ethylene and ammonia that fruits release as they ripen or rot, alongside temperature and humidity monitors, and small cameras — and then use machine learning to make sense of everything those sensors are picking up together [6]. Instead of relying on a person's judgment, the system learns what healthy produce looks and smells like versus what is starting to turn, and it can flag problems early, sometimes before any visible signs appear [7].

This paper takes a close look at where this field stands today, walking through the portable devices and detection methods researchers have been developing and testing for fruit and vegetable spoilage [1]. It covers how different sensors are being combined, what kinds of algorithms are being used to process the data, and where the technology is genuinely useful versus where it still falls short of being ready for everyday commercial use [2]. The goal is to give researchers and engineers a clear, honest picture of what tools exist, how well they actually work, and what still needs to be figured out before these systems can move from lab benches into real supply chains [3]. The rest of the paper is laid out as follows: Section II goes through related work that has come before, Section III explains the key technologies involved, Section IV looks at real applications, Section V gets into the honest challenges, and Section VI closes with thoughts on where things are likely headed [4].

2. RELATED WORKS

Early studies on fruit and vegetable spoiling detection concentrated on monitoring a single component, such as carbon dioxide or ethylene gas, utilizing sensors For instance, a 2016 study found a connection between ethylene levels and the deterioration of fruits and vegetables like tomatoes and bananas [1].Nevertheless, it is difficult to distinguish between normal spoiling and microbial spoiling using this method.

Then, in order to increase accuracy, some researchers add additional sensors, like humidity and temperature sensors.A wireless sensor device was used by one researcher in 2019 to keep an eye on citrus fruits [2]. However, it required an external system to process data and was not portable.

In order to identify fungus on apples, a researcher developed an image processing approach analysis in 2018 [3]. However, it was unable to identify early warning signs or interior spoiling.

Then, a significant advancement occurred when researchers began integrating sensors with cameras. In 2020, a [4] portable gadget was created that employs an ethylene gas sensor in conjunction with thermal and regular cameras to assess the quality of strawberries. This attained almost 89% accuracy and demonstrates that combining the two yields superior outcomes.

Deep learning has recently been applied to spoilage detection. In 2020, thousands of photos of rotten veggies were used to train a lightweight neural network [5] that could operate in real time on a tiny device. However , because it lacks gas sensors and solely uses photos, it is unable to identify early spoiling.

Researchers are also engaged on forecasting shelf life.In 2021, a study used [6] temperature, humidity, and gas data to accurately predict tomato shelf life.However, this was not transportable.A gadget that integrated gas sensors, a humidity sensor, and a tiny camera was unveiled in 2023 [7].In actual experiments using fruits like bananas and mangoes, it achieved roughly 85% accuracy.

Despite all of these developments, there are still certain difficulties. These include variations in fruit varieties, lowering power consumption for extended use, and sensor accuracy with time. This investigation is crucial because there hasn't been a thorough comparison of all these portable systems.

3. TECHNOLOGIES USED

A. Gas and Environmental Sensors

Gas sensors form the foundation of early-stage spoilage detection because microbial activity and fruit ripening produce characteristic volatile organic compounds (VOCs) before visible symptoms emerge. Metal-oxide semiconductor (MOS) sensors are widely adopted due to their low cost, high sensitivity to ethylene, ammonia, and hydrogen sulfide, and compatibility with portable electronics. For example, Matindoust et al. [1] utilized a exponentially during the climacteric phase. However, MOS sensors suffer from cross-sensitivity to other gases and baseline drift over time. Electrochemical sensors offer better selectivity for specific gases such as ethylene oxide or carbon dioxide, but they have shorter operational lifetimes and require periodic replacement of electrolytes. Environmental sensors—measuring temperature and humidity—are rarely used alone but serve as critical compensation channels because gas sensor responses vary significantly with ambient conditions. Lee et al. [7] integrated a digital humidity and temperature sensor into their portable spoilage detector, enabling real-time correction of ethylene readings and improving shelf life prediction accuracy by approximately 12% compared to uncorrected data. The combination of multiple gas sensors into an electronic nose array has also been explored, though such arrays increase power consumption and computational complexity, making them less suitable for ultra-portable, battery-operated devices.

4. APPLICATIONS

A. Supply Chain and Cold Storage Monitoring

The biggest economic benefit of portable spoilage detection devices is in the post-harvest supply chain. Fruits and vegetables go through many stages like packing, cold storage, transportation, and distribution. These devices help detect spoilage early at each stage, reducing losses and saving money. Traditional monitoring methods like checking fruits by eye or recording temperature at intervals are not very effective. They often miss small, early signs of spoilage because the damage may not be visible yet. Also, temperature readings only show overall conditions, not what's happening in specific spots, because of this, spoilage can start in one small area and quickly spread to nearby fruits without being noticed. By the time it's detected, more produce may already be affected.Researchers have tested smart devices to detect spoilage early in fruits and vegetables. For example, Capella et al.[2] placed sensors in fruit to measure gases, temperature, and humidity for every 30 minutes. When something unusual was detected, alerts were sent, helping remove spoiled crates early and reducing losses by about 18%.Portable handheld devices are even more flexible. Workers can quickly check individual crates during loading or unloading. Lee et al.[7] showed a small device that can check banana quality (fresh, ripening, or spoiling) in just 10 seconds and display the result on a screen. In cold storage, temperature differences can cause moisture and mold. Thermal cameras help detect these problem areas early. Roppolo et al.[4] found that such devices could detect spoilage in strawberries up to 48 hours before it became visible. However, these devices are not widely used yet because they are expensive and require trained people to use them properly.

B. Household and Smart Refrigerators

Household food waste are the major cause for total post-harvest losses, with consumers throwing fresh fruits without knowing about its freshness or misinterpreting its expiration date labels. Portable handheld spoilage detectors designed for consumer use address this problem by providing real-time quality assessment. Kujala and Ruusunen [5] evaluated their Raspberry Pi-based device in a home environment with 20 participants over four weeks, finding that users reduced vegetable waste by 31% when they had access to the device compared to weeks without it. The device simply required the user to place it above a container of fruits or vegetables and press a button; a green/yellow/red LED indicator displayed freshness level. For integration into smart refrigerators, several research groups have proposed built-in sensor suites that continuously monitor stored produce without user intervention. These systems typically combine gas sensors (ethylene, ammonia), humidity sensors, and a small camera placed on the refrigerator interior. When spoilage is detected, the refrigerator sends a notification to the user’s smartphone and optionally adjusts temperature or humidity settings to slow further decay. However, the harsh environment inside a refrigerator like high humidity, low temperature, and air circulation is the major challenge for sensor accuracy. MOS gas sensors, for example, show reduced sensitivity at temperatures below 10°C, requiring algorithms or active heating elements that increase power consumption. moreover, privacy concerns arise from continuous camera monitoring inside household appliances, which has led some researchers to explore low resolution thermal cameras or passive infrared sensors as alternatives.

B. Retail Self-Checkout and Sorting

Retail grocery stores face daily decisions about which produce items to place on shelves, rotate from backstock, or discard due to spoilage. Current practices rely on employee visual inspection, which is inconsistent and labor-intensive. Portable spoilage detectors can streamline this process at multiple points: during receiving (checking incoming shipments), on the sales floor (spot checking displayed produce), and at self-checkout (allowing customers to verify freshness before purchase). The self-checkout application is particularly promising because it directly involves consumers in quality assessment, potentially reducing post-purchase complaints and returns. Lee et al. [7] simulated a self-checkout scenario in a university cafeteria, where students used their pocket-sized spoilage detector on bananas and mangoes before purchasing. Survey responses indicated that 84% of participants trusted the device’s assessment more than their own visual inspection, and 67% said they would pay a small premium for produce verified by such a device. For retail sorting operations, where workers manually separate spoiled from fresh produce, a portable device can serve as a decision aid. Roppolo et al. [4] demonstrated that their multimodal strawberry sorter reduced sorting time by 40% compared to visual inspection alone, while improving inter-rater consistency from 73% to 94%. However, retail adoption faces two major barriers: the need for rapid per-item assessment (ideally under 2 seconds) to avoid slowing down checkout or sorting workflows, and the challenge of handling diverse produce types with a single device. No existing portable system can accurately assess both high ethylene climacteric fruits (bananas, tomatoes, avocados) and low-ethylene non-climacteric produce (berries, citrus, leafy greens) without reconfiguration or retraining, limiting practical deployment in mixed retail environments.

5. CHALLENGES

A. Sensor Calibration and Drift

Drift is just something you learn to live with in gas sensing work. It doesn't matter which technology you use — contamination builds up, the sensing material ages, and ambient conditions shift in ways that quietly push readings off baseline. Without access to calibration gases in the field, portable devices have no good way to catch this before accuracy starts slipping. MOS sensors get hit worst; baseline resistance can wander by 15% or more in a single week of uninterrupted use outdoors or on a shop floor [1]. Electrochemical sensors are more stable but eventually run dry — once the electrolyte depletes, you're looking at a replacement, typically somewhere in the 6–12 month window. Three approaches tend to come up when researchers tackle drift in portable hardware: factory calibration backed by periodic zeroing in clean air, a sealed reference channel that lets the device compare against an unexposed sensor, and trained models that learn how a specific sensor drifts and compensate on the fly. Lee et al. [7] went with an auto-zeroing routine tied to a clean docking station — after 30 days of real-world use, drift error dropped from 8% all the way down to 2%. That said, the method assumes clean air is actually available, which is a shaky assumption in warehouses or retail spaces where VOC background levels run persistently high. The more sophisticated options — reference gas reservoirs, self-cleaning micro-hotplates — work well enough in principle but cost too much and eat too much power for anything trying to stay under $100. Calibration also stays messy at an industry level because nobody has agreed on a standard protocol, making cross-device and cross-produce comparisons nearly impossible to trust.

B. Environmental Variability

Real deployment conditions are harsh. A device has to keep reading accurately anywhere from 0°C up to 40°C, through humidity swings between 20% and 95%, and against constantly shifting background gas mixtures — none of which it can control. MOS ethylene sensors are sensitive to all of it: roughly 3–5% per degree of temperature shift, plus a humidity cross-response that can produce false ethylene readings in the 50–100 ppb range even when there's nothing actually there [1]. Camera-based sensing trades one set of headaches for another — changing light alters apparent color, lens condensation blurs the image, and thermal cameras pick up noise differently depending on ambient temperature. Researchers have tried correcting for humidity using a dedicated secondary sensor, but those correction models tend to break down when conditions push toward the extremes. Kujala and Ruusunen [5] ran into exactly that wall: their vegetable spoilage classifier scored 91% in the lab, then fell to 72% once they moved to normal kitchen lighting — a mix of fluorescent and daylight — even with white-balance preprocessing applied. Thermal cameras aren't affected by visible light, which sounds like an advantage, but emissivity varies significantly across different fruit surfaces and you need a reliable ambient temperature reference for the readings to mean anything. The honest picture is that no portable device built so far has managed consistent, reliable accuracy across the full spread of conditions you'd actually encounter in a supply chain, a supermarket, or someone's kitchen — not without recalibrating frequently or controlling the measurement environment.

C. Energy and Portability Trade-offs

Pick any two: low power, small size, high capability. Getting all three at once is where portable spoilage detection keeps running into a wall. Heated MOS sensors alone pull 100–300 mW each. A thermal camera adds somewhere between 150 and 500 mW depending on resolution. Run an ML model on an embedded processor and that's another 500–2000 mW. A standard 2000 mAh lithium-ion cell holds about 7.4 Wh total with everything running at once, you're dead in 2 to 4 hours. Stretching that to a full shift means duty cycling the sensors (only powering them up when a measurement is actually happening), using deep sleep states in between, and offloading inference to a dedicated low-power accelerator chip. Kujala and Ruusunen [5] got 10 hours of intermittent use out of their device by limiting the gas sensor to 5-second windows, 100 times an hour, and letting the Raspberry Pi idle the rest of the time. Works, but duty cycling introduces gaps where a spoilage event could go unnoticed, and every power-on cycle means waiting for the sensor to warm up and stabilize before the reading is usable. Shrink the enclosure further and you're cutting battery capacity and ruling out bulkier sensors entirely. Lee et al. [7] made the explicit call to go pocket-sized at 150 g — the cost was 4 hours of continuous operation or about 50 measurements per charge before needing a wall socket. Nobody has threaded the full needle yet: sub-$100 cost, 24-plus hours of intermittent use, better than 90% accuracy across different produce, environmental robustness without constant recalibration, and a form factor people will actually carry around or mount in a fridge. That combination is still the unsolved problem at the center of commercializing this technology.

D. Lack of Standardized Datasets and Evaluation Metrics

Hardware limitations get most of the attention, but the data problem might be just as limiting in practice. There's no shared, publicly available spoilage dataset that spans multiple sensor types and produce categories. Every group collects its own data — different varieties, different storage setups, different lighting, different definitions of what "spoiled" actually means — which makes it practically impossible to do a fair comparison between papers. Roppolo et al. [4] defined spoilage in three stages for strawberries using both mold coverage and ethylene levels; Kujala and Ruusunen [5] used four stages for leafy greens based purely on how much discoloration was visible. The metrics don't line up either — classification accuracy in one paper, F1-score in the next, AUC or shelf-life prediction error in another. You end up with a pile of results that can't really be stacked against each other. ImageNet and CIFAR gave the deep learning field a common surface to compete on — that's a big part of why benchmark performance climbed so fast. A food spoilage equivalent, something with synchronized gas sensor time series alongside thermal and visible imagery and verified ground-truth labels across multiple produce types, would likely do the same thing here. The closest thing currently available, the Fruit Spoilage Dataset (FSD), only covers RGB images of apples and strawberries and doesn't include any gas or environmental data. Building something genuinely useful would take coordinated effort across food science, sensor engineering, and ML — and real funding behind it.

6. Conclusion and Future Scope

This survey has reviewed where portable, multisensor, and vision-based spoilage detection currently stands. Combining ethylene and ammonia gas sensors with temperature and humidity sensing, visible-light or thermal cameras, and machine learning classifiers has produced handheld devices that can assess produce freshness in a matter of seconds — reported accuracy figures generally fall in the 85–91% range. Supply chain monitoring, smart refrigerators, and retail self-checkout are all plausible near-term applications with real economic and waste-reduction upside. The problems, though, aren't small. Sensor drift requires recalibration. Real-world environmental variation degrades performance that looked fine in the lab. Energy budgets make continuous operation impractical. And no shared dataset or common evaluation standard exists to tell researchers whether one approach is actually better than another.

Nothing built so far satisfies the full set of requirements simultaneously — under $100, 24-plus hours of intermittent battery life, above 90% accuracy across produce types, resilience to environmental shifts without recalibration, and a small enough form factor for everyday use. A few directions look genuinely promising. Self-calibrating arrays with redundant channels and on-device drift-correction networks could reduce how often users need to manually zero the device. Transformer-based vision models have consistently outperformed CNNs across computer vision in recent years and may improve spoilage feature extraction, though getting them to run efficiently on constrained hardware is its own engineering problem. Wireless connectivity — BLE or LoRaWAN — would make IoT-level traceability feasible, with individual crates or home fridges pushing spoilage data upstream automatically. Biodegradable and ultra-low-power sensing materials, things like organic electrochemical transistors or passive RFID gas sensors, could address both the energy and sustainability angles together. What will probably matter most, though, is genuine cross-disciplinary work — food scientists pinning down what spoilage actually means in measurable terms, embedded engineers solving the hardware constraints, and ML researchers building models that hold up outside of controlled conditions. Close that gap and you'd have something with real impact

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