

# IoT-Based Artificial Olfaction Systems for Perishable Food Quality Monitoring: A Review and Classification

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## ABSTRACT

Food spoilage is a growing global issue, particularly for perishable foods such as meat, fruits, and grains, causing substantial losses in the supply chain. Standard quality verification usually relies on subjective organoleptic tests or laboratory techniques such as Gas Chromatography–Mass Spectrometry (GC-MS), which are cost-prohibitive and cannot be used in real time. In recent years, electronic noses (e-noses), which are Internet of Things (IoT)-based artificial olfaction systems, have emerged as effective, non-destructive tools for monitoring food quality.

This study reviews and classifies 35 peer-reviewed papers published from 2018 to 2026, examining sensor setups, processing platforms, machine learning methods, and IoT system designs. About half of the systems target meat and seafood, 30% focus on fruits and vegetables, and 20% on grains. Most meat and grain systems use Metal Oxide Semiconductor (MOS) sensors because they detect ammonia and amines well, while fruit monitoring systems mainly use ethylene-sensitive and environmental sensors. For data analysis, machine learning models such as Support Vector Machines (SVMs), Random Forests (RFs), and XGBoost often achieve high accuracy, and deep learning methods can reach up to 98% accuracy in complex spoilage situations.

The results show that a combination of different sensors, along with using edge computing platforms (like ESP32) increases the reliability and real-time performance of the system. Motivated by these findings, this paper presents an IoT E-Nose Design Framework (IENDF) to inform the design of scalable, application-specific systems.

**Keywords:** Artificial Olfaction, Electronic Nose, Internet of Things (IoT), Perishable Food Monitoring, Metal Oxide Semiconductor (MOS) Sensors, Machine Learning, Edge Computing, Food Spoilage Detection

## INTRODUCTION

Food wastage is a significant global issue with profound economic, environmental, and social implications. According to the Food and Agriculture Organization (FAO), approximately one-third of all food produced for human consumption globally, about 1.3 billion tons per year, is lost or wasted (FAO, 2011). In 2019, an estimated 931 million tons of food were wasted according to the United Nations Environment Programme (UNEP). In fact, according to more recent data (2022), 1.05 billion tons of food that could be eaten by humans - approximately 19% of all food available for consumption - are wasted globally, and households account for nearly 60% percent of this waste (UNEP, 2021; UNEP, 2024). Contrary to waste-reduction efforts, issues with monitoring the quality of perishable foods, including meat, fruits, and grains, continue to cause significant losses.

Most current food quality checks are performed manually. Human sensory tests are subjective and observer-dependent, while lab methods such as Gas Chromatography–Mass Spectrometry (GC-MS) techniques offer accuracy but are expensive, time-consuming, and impractical for real-time or field applications. These challenges complicate the development of scalable, continuous, and low-cost monitoring systems for perishable food.

Artificial olfaction systems (electronic noses, or e-noses) have become increasingly feasible with recent developments in embedded systems, sensors, and the Internet of Things (IoT). These devices identify volatile

organic compounds (VOCs) emitted as food decays and convert them into electrical signals for analysis. With inherent advantages such as lower cost, portability, real-time monitoring, and the ability to connect to wireless networks, IoT-enabled e-nose systems offer significant improvements over traditional methods.

Furthermore, despite rapid technological advancements, standardized engineering procedures for IoT-based e-nose systems across various food types remain lacking. Most studies rely on single examples and thus offer limited insight into the optimal mix of sensors, processing platforms, machine learning models, or system designs. This heterogeneity hinders the reproducibility of results, the scale-up of solutions, and their deployment in real-world settings like cold chain logistics.

To fill this gap, the present study presents a systematic literature review and an engineering classification of IoT-based artificial olfaction systems for monitoring perishable food. Specifically, it aims to:

- (1) provide a review of the state-of-the-art sensor technologies and associated spoilage markers;
- (2) assess the effectiveness of machine learning algorithms for classification and prediction;
- (3) characterize IoT system architectures and processing platforms; and
- (4) propose an IoT E-Nose Design Framework (IENDF) that allows for guiding future research and system development.

This helps establish a solid technical foundation for developing efficient, scalable, and application-specific food quality metric systems that align with global sustainability targets by synthesizing recent findings and identifying key design patterns and limitations.

## METHODOLOGY

### Research Design

Using a systematic descriptive-analytical review, this work aims to identify, evaluate, and classify IoT-based artificial olfaction systems for monitoring perishable foods. The method is guided by a clear review process with steps for each of finding, screening, assessing, and extracting data from the literature to ensure transparency and reproducibility. The researcher employed an engineering classification strategy to parse system architectures, sensor configurations, and algorithms identified in the chosen studies.

### Data Sources

Relevant literature was collected from established scientific and engineering databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. These databases were selected for their comprehensive coverage of research on the Internet of Things (IoT), embedded systems, sensor technologies, and machine learning, all of which are essential to the development of artificial olfaction systems. Accessing these sources ensured the inclusion of peer-reviewed journal articles and conference papers, thereby supporting a comprehensive and credible literature review.

### Search Strategy

A structured, keyword-based search strategy was employed to systematically identify studies related to IoT-based artificial olfaction systems. The search used combinations of key terms, including “electronic nose” or “artificial olfaction,” “Internet of Things” or “IoT” or “wireless sensor,” and “food spoilage” or “food freshness” or “quality monitoring.” Boolean operators were applied to construct the comprehensive search query: (“electronic nose” OR “artificial olfaction”) AND (“IoT” OR “wireless sensor”) AND (“food spoilage” OR “freshness detection”). This approach ensured broad yet targeted coverage of relevant literature across multiple disciplines. To remain relevant to recent technological advancements, the search was restricted to publications from 2018 to 2026.

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## Study Selection Process

The study selection process used several screening steps:

**Step 1 - Initial Identification:** Approximately 120 studies were identified across all databases.

**Step 2 - Duplicate Removal:** After removing duplicates, 95 unique studies remained.

**Step 3 - Title and Abstract Screening:** We screened the studies for relevance to IoT-based e-nose systems, narrowing the list to 60.

**Step 4 - Full-Text Eligibility Assessment:** Full-text articles were evaluated against predefined inclusion and exclusion criteria, resulting in a final set of 35 studies.

## Inclusion and Exclusion Criteria

The diversity of the interdisciplinary literature under review necessitated clearly defined inclusion and exclusion criteria throughout the review process to safeguard consistency, relevance, and technical rigor. The inclusion criteria were peer-reviewed journal articles and conference papers on IoT-based electronic nose systems. Eligible studies combined gas sensors with microcontrollers or embedded platforms and presented sufficient technical detail on system design, implementation, or performance evaluation.

On the other hand, studies based solely on biological or chemical analyses without an embedded/IoT-based system were not considered. Studies based solely on large laboratory apparatus (e.g., Gas Chromatography–Mass Spectrometry [GC-MS]) and without any portable or embedded schemes were excluded. In addition, we omitted non-English publications and review articles that did not describe the technical systems in detail to avoid ambiguity in our results or inconsistencies between methodologies.

## Data Extraction and Classification

A structured data extraction form, based on validated review frameworks, was used to systematically collect information from each study. The data were categorized into the following key dimensions:

- Sensor Configuration: type of sensors and target gases (e.g., ammonia, ethylene)
- Processing Platform: microcontrollers and embedded systems (e.g., Arduino, ESP32, Raspberry Pi)
- Data Processing Techniques: machine learning and signal processing methods
- IoT Architecture: communication protocols and system deployment models
- Performance Metrics: accuracy, precision, latency, and computational requirements
- Application Domain: meat, fruits, vegetables, or grains

The data were organized into comparative matrices to support cross-study analysis.

## Data Analysis

Descriptive and comparative analytical methods were used to identify trends, patterns, and performance tradeoffs across the selected studies. The analysis included frequency analysis to examine the distribution of specific sensors, platforms, or machine learning algorithms, and comparative evaluation to quantify performance differences across multiple models and system architectures. Moreover, relationships among food categories, sensor types, and computational methods were analyzed using cross-tabulation. Furthermore, a gap analysis was performed to highlight shortcomings of current systems regarding the practical deployment challenges and energy efficiency issues. This example multi-dimensional approach facilitated the creation of a formalized

engineering taxonomy and helped develop actionable design guidelines for emerging IoT-based artificial olfaction systems.

### Ethical Considerations

This work drew solely from peer-reviewed academic scholarship in the public domain. Formal ethical approval was not required, as this involved no human participants or sensitive data. Citation and referencing were meticulously adhered to uphold academic integrity.

## RESULTS AND DISCUSSION

After following the systematic selection process, the researcher analyzed 35 studies, of which about half focused on meat and seafood, 30% on fruits and vegetables, and 20% on grains. These materialized results are reframed through a comparative, engineering-centric lens, focusing on system design trade-offs, performance characteristics, and practical limitations.

### Sensor Array Architectures

The choice of suitable sensors to be employed in different studies will vary greatly based on the food type and relevant spoilage markers. In the context of meat and seafood, Metal Oxide Semiconductor (MOS) sensors such as the MQ-136 and MQ-137 were most frequently used for their sensitivity to ammonia (NH<sub>3</sub>) and trimethylamine (TMA), which are important markers of protein degradation. Studies such as Damdam et al. On the other hand, effective spoilage classification using MOS-based systems integrated with ESP32 and Arduino platforms was presented by Prasai et al. (2023) and Binson and Thomas (2023), respectively.

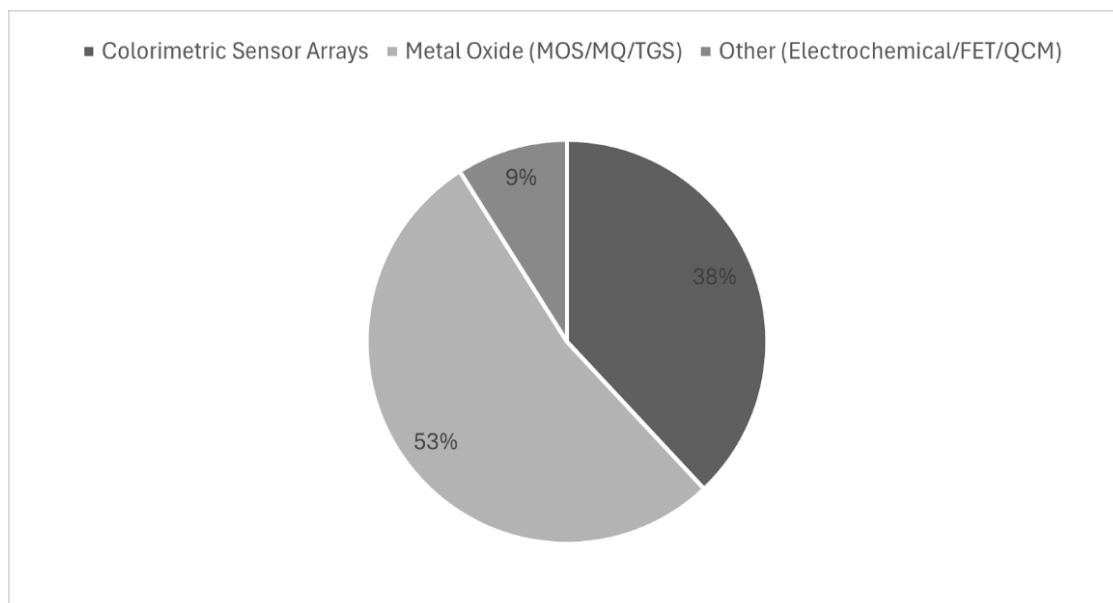


Figure 2: Distribution of Sensor Types for Meat

MOS sensors can be produced at low cost while still delivering good sensitivity and ease of integration for IoT deployment. Yet, these benefits have come at a cost, with high power consumption due to heating requirements, as well as susceptibility to sensor drift and limited selectivity, which can affect long-term reliability in real-world environments.

Novel alternatives, including piezoelectric micro-cantilever sensors (Ferrier et al., 2024), offer superior specificity for detecting compounds such as cadaverine but entail higher complexity and expense, limiting their use in low-cost IoT systems. It also helps with collimation and filtering of signals from multiple sources, enabling accurate detection of blended signal sources (Kodogiannis & Alshejari), but it comes at the cost of greater computational overhead and more complex system integration, as multispectral imaging-based methods do not integrate well with MOS sensors.

In sensor architectures for Internal presence of fruit, the ability to detect  $C_2H_4$  and fermentation-associated gases. Studies such as Haque et al. (2025) and Febriana et al. utilized environmental sensors (e.g., DHT11/DHT22), in addition to gas sensor units, as this method allows for a more realistic modeling of respiration of fruits, which is strongly temperature-dependent. Multi-sensor fusion increases prediction accuracy but adds data fusion complexity and calibration requirements that must be performed dynamically under changing environmental conditions.

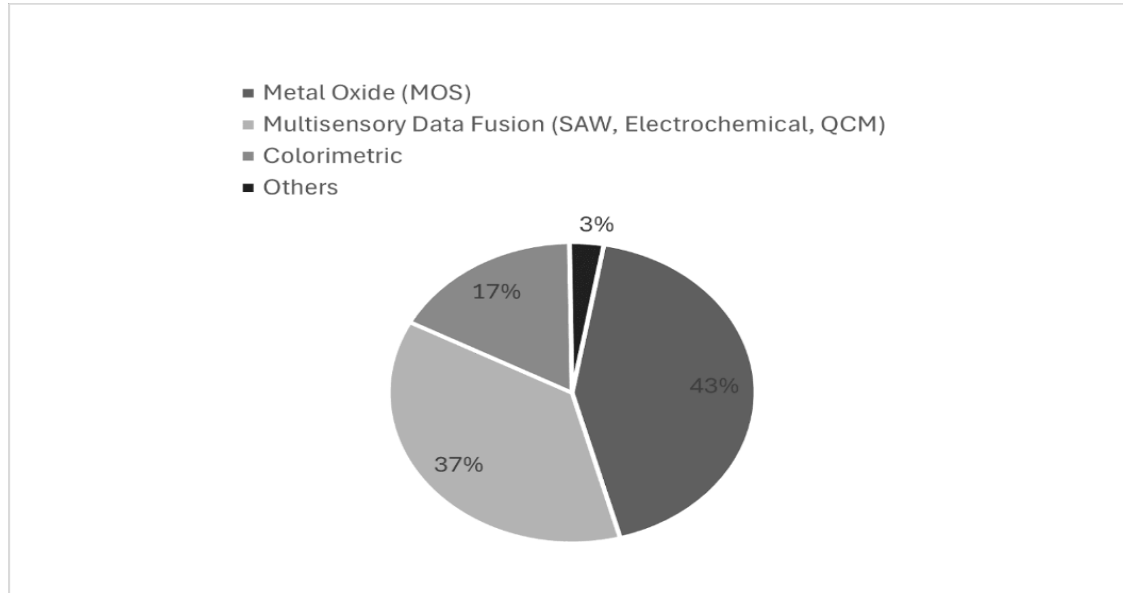


Figure 3: Distribution of Sensor Types for Fruits

Fungal VOCs are difficult to detect; very sensitive monitoring systems for the grain environment should be developed. Other studies used arrays of 10 MOS sensors and validated the techniques using GC-MS (Jiarpinijnun et al., 2020). Although this enhances detection precision, it also leads to higher system cost, increased energy consumption, and scalability challenges, especially for larger storage facilities.

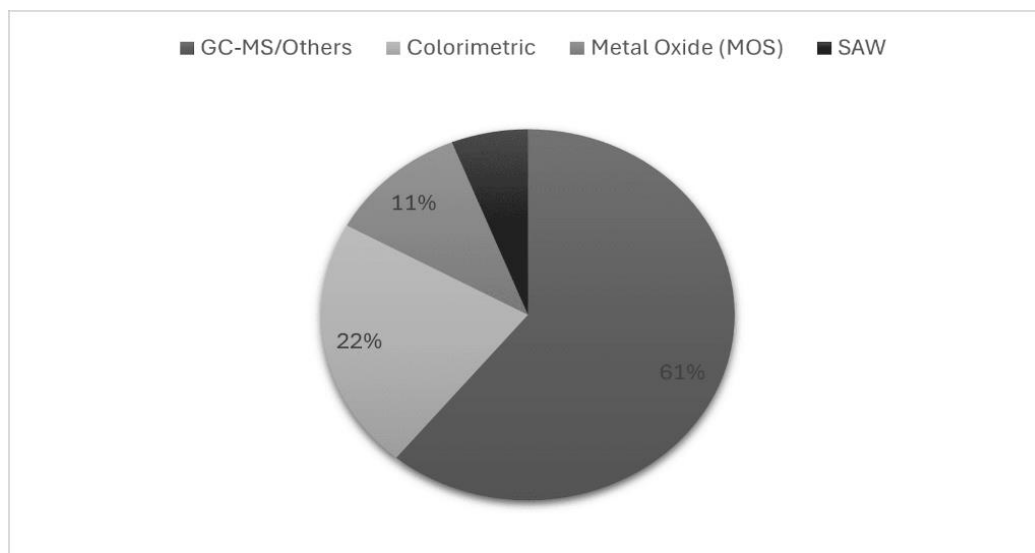


Figure 4: Distribution of Sensor Types for Fungal VOCs

### Performance of Intelligent Classifiers

Various machine learning models have been used to classify food freshness and predict spoilage levels. One of the most commonly used models is still Support Vector Machines (SVM) because they work well with high-dimensional sensor data. But new trends suggest a transition towards more sophisticated models, including ensemble learning methods and deep learning layers.

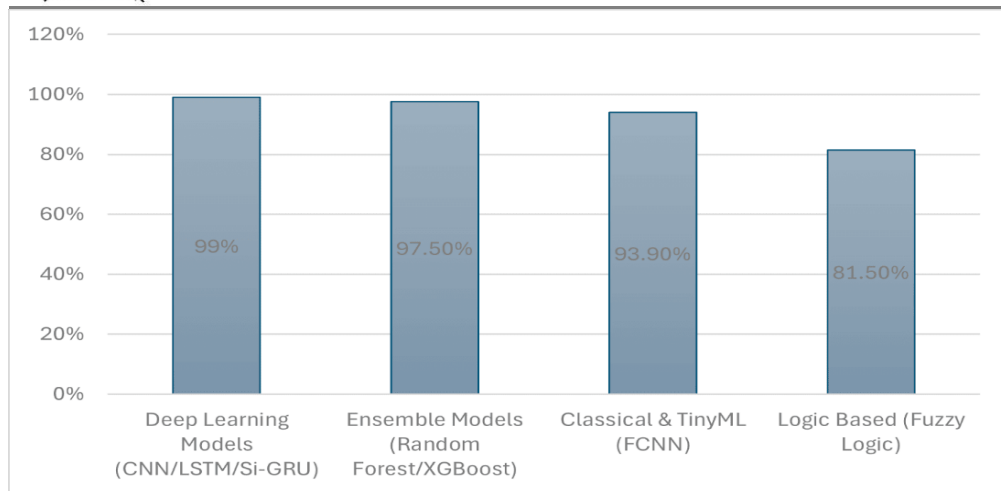


Figure 5. Comparative Accuracy of AI Models

Extreme Gradient Boosting (XGBoost), as presented in Setyagraha et al. (2025), confirms this finding by achieving virtually perfect classification accuracy (100% for accuracy, precision, and recall, respectively) with very low computational cost ( $\approx 1$  ms inference time and  $\approx 4$  kB memory). This makes it ideally suited for edge computing applications where resource efficiency is of the utmost importance.

Meanwhile, deep learning rules (CNN-LSTM and Si-GRU architectures) (Guo et al., 2025; Liu et al., 2024), resulted in even higher accuracy up to 98% with proven strength in their ability to model complex non-linear relationships from sensor data. But these models come with important engineering trade-offs: they can be computationally expensive, energy hungry, and require large datasets — factors that inhibit their adoption for low-power microcontroller deployment.

To overcome these limitations, the latest research focuses on TinyML approaches that run lightweight neural networks on embedded targets. Haque et al. (2025) demonstrated a quantized neural network achieving 91.9% accuracy in predicting a device's shelf life with limited hardware resources. This technique is applied to increase efficiency at the expense of accuracy compared with full-scale deep learning models.

Yoo (2025) reported a low Mean Absolute Error (MAE) of 0.05 using Gaussian Process Regression (GPR) for shelf-life prediction. While GPR is highly accurate, it is known to suffer from scalability issues and computational bottlenecks for large datasets, factors that hamper its deployment in real-time IoT systems.

### Integrated IoT Architectures

This is a critical decision regarding the performance, scalability, and deployment of the overall system. Due to their simplicity and strong conventional support, Arduino-based systems are still widely used for rapid prototyping. But they are not powerful and have no native connectivity.

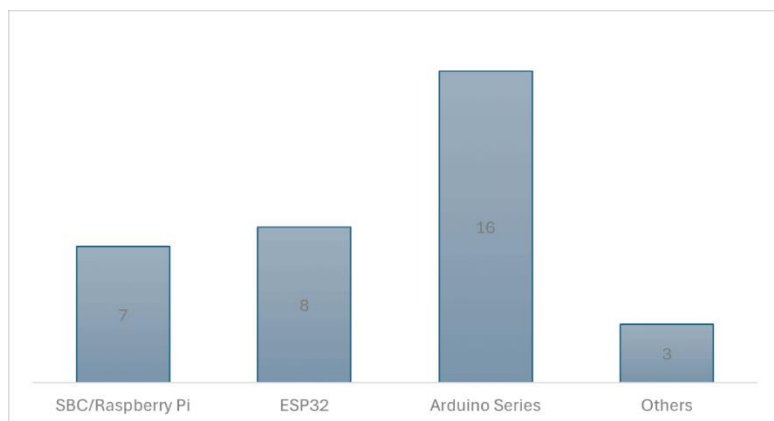


Figure 6. Taxonomy of Processing Units

There is indeed a trend towards such ESP32-based architectures, as shown by Damdam et al. (2023) and Febriana et al. (2025), which are particularly suitable, as they possess features such as dual-core processing power, integrated Wi-Fi/Bluetooth, and suitability for edge AI applications. The combination of these features enables wireless, real-time data processing and communication, making the ESP32 well-suited for scalable IoT deployments.

By contrast, systems built on the Raspberry Pi are better suited for applications that require higher processing power, such as multimodal sensor fusion with imaging data. These systems offer improved processing power; however, they are susceptible to trade-offs involving excessive power draw, elevated cost, and diminished portability, which can constrain their implementation in distributed or battery-powered environments.

Data processing is one of the core areas of data science from an architectural point of view, so the adoption of edge computing has also been a key trend, ensuring local data processing to minimize cloud dependency. This leads to increased responsiveness in the system with lower latency, while also posing a challenge for algorithms on resource-constrained devices, as care must be taken to ensure they run within the given constraints.

## Gap Analysis and Limitations

While there have been considerable improvements in existing IoT-based e-nose systems, some limitations still remain. First, most studies are performed in laboratory settings with limited validation in real-world environments such as transport and storage facilities. Environmental issues, including temperature changes, humidity levels, and sensor drift, can have a major impact on system performance but often are not handled properly.

The second key issue is that power consumption remains a major challenge, especially for MOS-based systems, which require continuous heating. This renders them less suitable for deployment in long-term, battery-powered logistics applications.

First, there is little standardization in system design, sensor selection, data processing methods, and evaluation metrics. This complicates the comparison of results across studies and limits the development of scalable, interoperable solutions.

Third, while high accuracy is achievable using state-of-the-art machine learning models, in most cases, their computational cost makes real-time edge deployment infeasible; the trade-off between hardware costs vs. model performance should be further explored and understood.

## CONCLUSION AND RECOMMENDATIONS

### Conclusion

This study provided a systematic review and classification of IoT-based artificial olfaction systems designed for monitoring the quality of perishable food, offering an engineering-oriented overview of current design trends and technological developments. The results demonstrate that system effectiveness is largely context sensitive, reflecting successful implementation of the sensor arrays, processing platforms, and machine learning models specific to food items.

Although MOS sensors offer sensitive and low-cost solutions for detecting meat and grain, the need to increase the power supply requirements of these systems, as well as their susceptibility to drift, limits long-term implementations. The fruit ambient gas and environmental monitoring in the sensor fusion domain becomes crucial for context-aware and robust prediction. One class of models that offer a great compromise in accuracy and processing time (due to the lightweight nature) are XGBoost, or even SVMs, both of which allow good performance while keeping the model capable of being realized at edge, on the other hand with deep learning we find better accuracy but increased resource requirements for processing (bound to bandwidth and connectivity).

In other words, from a system architecture perspective, ESP32-based platforms are the only truly scalable solution for IoT because they combine connectivity with edge intelligence. Still, the highly accurate capture of real-world environments introduces problems with sensor stability, dynamic component variability, and energy consumption that must be addressed before the method can be applied in practice.

In summary, this study demonstrates that optimal designs of effective IoT-based e-nose systems must follow a co-optimization paradigm across sensing, computation, and communication layers. The IoT E-Nose Design Framework (IENDF), presented in this work, offers a structured approach to the design of advanced electronic nose solutions that are scalable, efficient, and application-specific; a step towards realizing intelligent food quality monitoring systems.

## Recommendations

This paper proposes several engineering recommendations for IoT-based artificial olfaction systems, informed by its findings.

It is evident that, for the purposes of capstone and system implementation, it would be advisable to use ESP32-based platforms with multi-sensor arrays, particularly for MOS-based gas detection and environmental sensors for contextual monitoring. Lightweight machine learning models, viz. XGBoost, SVM, or optimized TinyML architectures, as edge deployment solutions, can perform real-time processing with minimal latency and cloud dependency. Modularity should be a core concept when designing the system, as it would allow for platform scaling and the inclusion of additional sensing modalities in the future.

Future studies should focus on real-world validation in dynamic contexts such as transport, storage, and different environmental conditions. In summary, for experimental designs in our work to perform consistently in non-laboratory settings, the effects of multiple changing conditions, such as sensor drift, temperature variability, and humidity variation, must be explicitly accounted for. This involves establishing standardized evaluation metrics and benchmarking protocols to improve comparability across studies.

Power Consumption as a Primary Design Constraint on Hardware and System Optimization. Future systems should investigate low-power or unheated gas sensors, duty-cycling strategies, and energy-efficient communication protocols to facilitate long-term battery-powered operation. There may also be a need to explore hybrid architectures that leverage computational efficiencies from edge computing while infusing advanced analytics processes from the cloud.

In summary, the researchers conclude that building a proper IoT-based e-nose system requires co-designing the sensing, computation, and communication layers to achieve performance goals while addressing scalability and energy efficiency.

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