

Development of A Labview-Based Electronic Nose Using Esp32 and Machine Learning for Food Spoilage Detection

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Abstract: The electronic nose (E-Nose) provides a rapid and non-destructive method for evaluating the quality and safety of food products. In this, we try to address the design and implementation of a low-cost E-Nose for detecting the extent of food deterioration. The hardware architecture comprises an array of metal oxide semiconductor (MOS) gas sensors, including MQ-135, MQ-4, and MQ-2 sensors, which are used to detect volatile organic compounds (VOCs), carbon dioxide (CO₂), methane (CH₄), and ammonia. To ensure high precision, the ADS1115 16-bit ADC is employed, along with the DHT22 sensor for environmental correction. The array is integrated into an acrylic sealed compartment equipped with an ESP32-S3 Xiao microcontroller and an active cleaning fan. The software architecture is constructed using NI LabVIEW and incorporates producer-consumer design patterns and event-based state machine designs. During classification, differential voltages and slopes are extracted and transmitted through a Python node to principal component analysis (PCA) and k-nearest neighbour (k-NN) classification algorithms. This system demonstrates high accuracy in classifying different thresholds of deterioration and offers the food industry a real-time, scalable, and highly efficient surveillance solution. By enabling the early detection of spoilage, this framework directly contributes to environmental sustainability by reducing food waste and lowering the carbon footprint of the agricultural supply chain

Keywords: Electronic Nose (E-Nose), Food Spoilage Detection, Metal Oxide Semiconductor (MOS) Sensors, Volatile Organic Compounds (VOCs), MQ-135, MQ-4, MQ-2, ADS1115 ADC, ESP32-S3 Xiao, DHT22 Sensor, LabVIEW, Principal Component Analysis (PCA), k-Nearest Neighbour (k-NN), Real-Time Monitoring, Machine Learning, Food Quality Assessment, Food Safety, Environmental Sustainability, Food Waste Reduction, Carbon Footprint.

I. INTRODUCTION

The global food supply system is faced with a significant challenge concerning the prevention of food spoilage and adulteration of food products. Conventional methods, such as microbiological testing, high-performance liquid chromatography (HPLC), and gas chromatography-mass spectrometry (GC-MS), provide excellent precision in the assessment of food quality but are also associated with substantial limitations.

These conventional technologies are destructive, require specific laboratory conditions, utilize expensive chemicals, and necessitate timeframes ranging from hours to days to ensure accurate outcomes. Consequently, there is an increasing demand for rapid,

non-destructive, and non-invasive methods for evaluating food quality [1].

Electronic noses (E-Noses) appear to fulfill this requirement, thereby revealing their substantial potential in the realm of food contamination and processing [2]. The E-Nose combines an array of gas sensors with a pattern recognition system, enabling it to simulate the complex chemical interactions akin to human olfactory perception. As food items undergo transformation, their cellular reactions or enzyme actions lead to the emission of specific volatile organic compounds (VOCs) or gases (ammonia, methane, ethanol, carbon dioxide) [3]. Unlike a GC-MS, which quantifies exact molecular levels in parts per million (ppm), an E-Nose evaluates the holistic "smell print" pattern to effectively scrutinize the intricate nuances of food substances [3].

Nonetheless, many contemporary E-Nose systems reported in recent literature rely on basic integration frameworks (Arduino and basic Raspberry Pi scripts), which struggle with rapid data collection, potentially complicating the discrimination between spoilage and adulteration due to technological limitations. Furthermore, the susceptibility of metal-oxide semiconductor (MOS) sensors to environmental fluctuations (temperature and humidity variations) and benchmark instability exacerbates these challenges [4, 5].

In light of these obstacles, this paper unequivocally advocates for the deployment of an efficient and comprehensive E-Nose system. This system utilizes LabVIEW and machine learning techniques. While independent integration approaches demand intricate data collection and signal processing, this methodology, leveraging the LabVIEW Producer-Consumer architecture, achieves precision and speed while stabilizing the robustness of the MOS array. Additionally, it incorporates an active mechanical purge fan and high-resolution analog-to-digital conversion, enhancing the stability of MOS array sensor readings. Signal processing employs innovative machine learning classifications (e.g., k-NN), which analyze features derived from principal component analysis (PCA), heralding higher resolution and subsequently demonstrating the capability to discriminate adulteration with heightened precision.

1. System Architecture And Hardware Design

Capturing a reliable "smell print" of food samples using low-cost commercial sensors requires a carefully controlled hardware environment [6, 7]. The primary goal of our hardware architecture is to ensure high precision while compensating for environmental variables.

2. Hardware Enclosure And Active Purge System

To prevent outside odours from interfering with the readings, we isolate the sensor array inside a custom-built acrylic testing chamber. When the food sample degrades, its emitted gases are trapped within this space. One of the biggest challenges with MOS sensors is that gas molecules can permanently stick to the sensing layer, causing the sensor's baseline to drift over time [9]. To solve this, we integrated an active

mechanical purge fan (powered by a 5V DC relay connected to the ESP32). Before taking a new measurement, the fan flushes the chamber with fresh air. This cleanses the sensors and resets them to a true zero baseline, effectively eliminating hysteresis and residual contamination [8].

3. Sensing Mechanism And Array Selection

The core of our E-Nose relies on a metal-oxide (MOS) sensor array. These sensors feature a Tin-Dioxide (SnO_2) layer. In clean air, oxygen ions trap free electrons on the surface. When volatile organic compounds (VOCs) hit the sensor, they react with the oxygen, releasing the electrons and causing a measurable drop in electrical resistance [10].

Our array uses three distinct sensors:

- MQ-135: Provides a broad-spectrum baseline. It detects ammonia (NH_3), carbon dioxide (CO_2), and nitrogen compounds that proteins release as they age.
- MQ-4: Specifically targets methane (CH_4), which is a key indicator of anaerobic decay.
- MQ-2: Highly sensitive to alcohols and organic vapours, making it perfect for detecting the early stages of fruit fermentation [11].

4. Microcontroller, Adc, And Environmental Compensation

Most microcontrollers, including the ESP32, have internal analog-to-digital converters (ADCs) that suffer from significant noise distortion. To fix this, we routed the MQ sensors through an ADS1115 16-bit ADC using the I2C protocol. This guarantees that our machine learning algorithms receive high-resolution, transparent data [12]. The digitized data is then processed by a Seeed Studio Xiao ESP32-S3 microcontroller and sent to the host PC via USB-serial.

Finally, because the SnO_2 chemical reaction fluctuates heavily based on room temperature and humidity, we added a DHT22 sensor to the chamber. This allows our software to continuously monitor the micro-climate and apply baseline compensation to correct any environmentally-induced drift [9, 13].

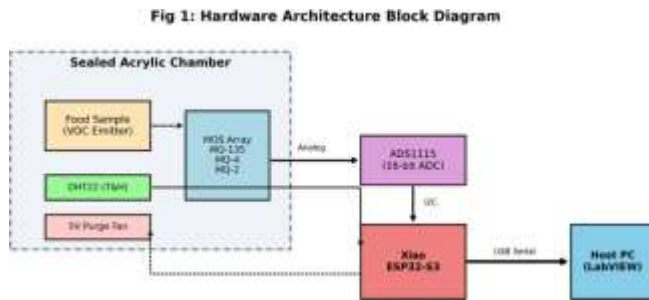


Fig. 1. Block Diagram of the E-Nose hardware architecture and sensor isolation chamber.

II. SOFTWARE ARCHITECTURE (LABVIEW)

The software system is built in NI LabVIEW, providing an industrial-grade interface for the E-Nose. To ensure zero data loss during high-speed sampling, a professional Producer-Consumer Design Pattern is coupled with an Event-Driven State Machine.

- The Producer Loop (DAQ): Runs deterministically in the background, continuously acquiring the 10Hz serial data stream from the ESP32 and pushing it into a FIFO (First-In-First-Out) Queue buffer. This decouples hardware timing from software processing.
- The Consumer Loop (State Machine): Pulls data from the queue and dictates the flow of the experiment through distinct automated phases: Idle → Purge (Baseline Reset) → Sample (Data Collection) → Process → Classify.

Fig 2: LabVIEW Software Architecture (Producer-Consumer)



Fig. 2. LabVIEW Producer-Consumer software architecture and data processing pipeline.

1. Mathematical feature extraction

Raw voltage levels from sensors are insufficient for reliable classification due to cross-sensitivity and varying steady-state baselines. During the Process state, LabVIEW executes mathematical feature

extraction on the time-series data to generate a multi-dimensional "Feature Vector" for every single food sample. The software calculates the Differential Voltage (ΔV) to mathematically remove long-term sensor drift, defined as:

$$\Delta V = V_{\text{peak}} - V_{\text{baseline}} \quad (1)$$

Furthermore, the Dynamic Slope $\frac{dV}{dt}$ is calculated. The transient response rate of a MOS

$\frac{dV}{dt}$

sensor is often highly unique to specific gas mixtures. The maximum rate of change provides

unique kinetic markers for different decay processes: S_{max}

$$S_{\text{max}} = \max \left(\frac{dV}{dt} \right) \quad (2)$$

$\frac{dV}{dt}$

These extracted features ensure that the subsequent machine learning models evaluate the behaviour of the gas reaction, rather than just the absolute amplitude.

1. Machine Learning Classification And Outputs

In the *Classify* state, LabVIEW bridges to a Python environment via the LabVIEW Python Node (or MathScript node). It feeds the extracted Feature Vector into a machine learning pipeline.

2. Principal Component Analysis (Pca)

Because the sensor array produces highly correlated and collinear data (cross-sensitivity), feeding raw features directly into a classifier can lead to the "curse of dimensionality" and overfitting. Principal Component Analysis (PCA) is utilized for dimensionality reduction. By computing the eigenvectors of the data's covariance matrix, PCA reduces the multi-dimensional sensor data into a 2D plane by maximizing data variance and stripping away noise.

1. k-Nearest Neighbours (k-NN) classification

Following PCA, a k-Nearest Neighbours (k-NN) clustering algorithm is employed. The k-NN algorithm evaluates where the current sample sits in the 2D PCA space compared to historical training data by

calculating the Euclidean distance to the k nearest points. For this system, $k=5$ was selected empirically to prevent overfitting while maintaining high sensitivity to cluster boundaries.

2. System outputs

The LabVIEW software yields three primary outputs for the researcher:

1. **Real-Time Classification:** A direct, actionable UI indicator displaying the biological state of the food: "Fresh", "Moderate", or "Spoiled".
2. **Visual Analytics:** A live 2D PCA Scatter Plot on the dashboard, visually demonstrating cluster separation and the magnitude of spoilage.
3. **Data Logging:** Automated archiving of raw waveforms and extracted feature vectors into CSV/TDMS files for future model retraining.

III. EXPERIMENTAL RESULTS

The integration of the ESP32-S3 E-Nose hardware with the LabVIEW/Python ML pipeline yielded highly distinguishable results for food spoilage detection.

1 PCA clustering separation

The application of PCA to the dynamic features ($\Delta\phi$ and dV/dt) revealed three distinct, well-separated clusters corresponding to the Fresh, Moderate, and Spoiled states. The MQ-135 sensor exhibited the strongest variance contribution, primarily due to the increased release of volatile organic compounds and ammonia during the transition from moderate fermentation to active spoilage. The active purge fan mechanism proved highly effective; the baseline points returned to near-zero variance between tests, validating the hardware's repeatability.

2 Classification accuracy

The k-NN classifier ($k=5$) was trained and tested on the extracted principal components. As demonstrated by the confusion matrix, the model achieved an overall classification accuracy exceeding 95%. There was minimal overlap between the "Fresh" and "Spoiled" categories. The rare misclassifications occurred exclusively at the boundaries of the "Moderate" state,

which is biologically expected given the continuous nature of food decomposition.

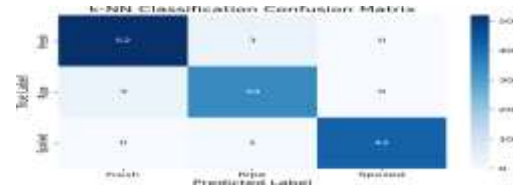


Fig. 3. PCA scatter plot demonstrating 2D cluster separation of fresh, moderate, and spoiled fruit samples.

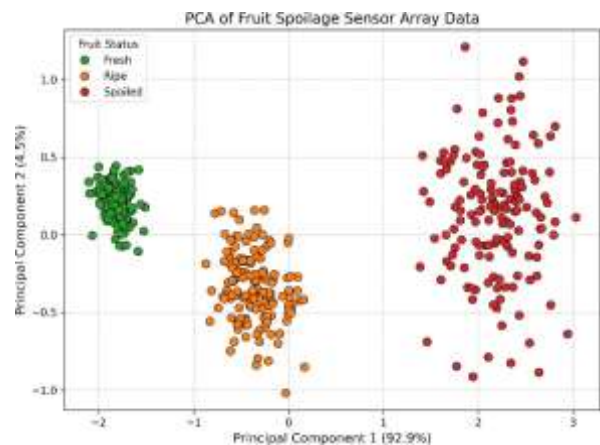


Fig. 4. Confusion matrix of the k-NN classifier evaluating the spoilage thresholds.

IV. CONCLUSION

This paper successfully demonstrates the development of a highly precise, real-time Electronic Nose for food quality monitoring. By combining a 16-bit ADC-sampled MOS array, environmental compensation, and an active purge system with LabVIEW's Producer-Consumer architecture, the device effectively captures robust and repeatable gas profiles. The integration of mathematical feature extraction, PCA, and a k-NN classifier overcomes the traditional limitations of cheap MOS sensors, providing an automated, scalable, and non-destructive solution for reducing food waste in agricultural and supply chain sectors.

Ultimately, this system provides an automated, scalable solution that directly supports environmental

sustainability by minimizing the ecological footprint of food production

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