E-Nose: Automated Food Spoilage Detection via Multi-Sensor Fusion and Deep Learning

Noah Raupold
Student ID 5022097
University of Applied Sciences
Würzburg-Schweinfurt

David Gläsle
Student ID 5022114
University of Applied Sciences
Würzburg-Schweinfurt

***Abstract*—This paper presents the design and implementation of an electronic nose (E-Nose) for automated food spoilage detection. The system combines an NDIR CO_2 sensor (SCD30) with a metal-oxide gas sensor (BME688) to capture volatile organic compounds (VOCs). Time-series data is analyzed using a Masked Autoencoder (MAE) approach that learns normal atmospheric patterns through self-supervised learning. Anomalies caused by fermentation or decay are identified via elevated reconstruction errors. Our measurements demonstrate that gas resistance drops by a factor of 1000 during mold contamination (from 100 kΩ–10 MΩ to 5–30 kΩ), enabling reliable classification.**

***Index Terms*—Electronic Nose, VOC Detection, Food Spoilage, Masked Autoencoder, Time Series Anomaly Detection**

I. Introduction

Food waste represents a global challenge with significant economic and environmental implications. A substantial portion of household food spoilage occurs unnoticed in closed storage environments such as refrigerators. While the human eye can detect visible mold, early chemical indicators of decay – such as elevated CO_2 from bacterial respiration or the release of specific gases – often remain undetected for extended periods.

The primary objective of this work is the **early detection of food spoilage** through a sensor-based system. Since microorganisms release metabolic byproducts into the surrounding air during early growth phases, decay can be detected before it becomes visually or olfactorily perceptible.

II. Methodology

A. Sensor Hardware

The system employs two complementary sensors communicating via I^2C bus with a Raspberry Pi (Fig. 1).

1) SCD30 – NDIR CO_2 Sensor: The Sensirion SCD30 [1] utilizes non-dispersive infrared absorption (NDIR) for precise CO_2 measurement. CO_2 molecules absorb light at 4.3 μm, enabling selective detection without the cross-sensitivities of electrochemical sensors. Many aerobic spoilage organisms produce CO_2 as a metabolic byproduct, leading to measurable concentration increases in closed containers.

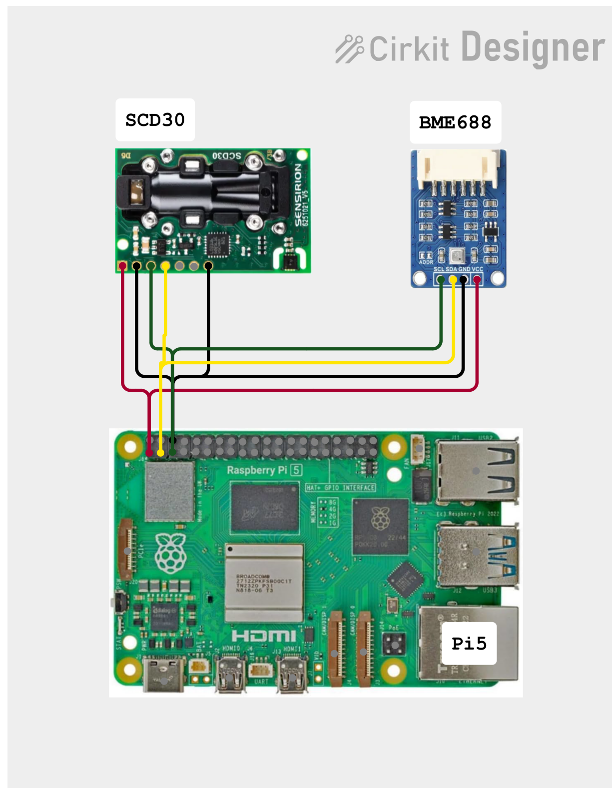

Figure 1. Circuit diagram of I^2C sensor connections

2) BME688 – MOX Gas Sensor: The Bosch BME688 [2] is a metal-oxide semiconductor sensor (MOX) for detecting volatile organic compounds (VOCs) [3]. During protein and fat decomposition, characteristic compounds such as ethanol, acetaldehyde, ammonia (NH_3), and hydrogen sulfide (H_2S) are released.

Operating Principle: The sensor contains a heated tin oxide layer (SnO_2). In clean air, this exhibits high electrical resistance. Upon contact with reducing gases, they react with the surface and release electrons – resistance decreases proportionally to VOC concentration.

3) Sensor Complementarity: Combining both sensors is essential: CO_2 alone is insufficient for spoilage detection, as both fresh fruits (cellular respiration) and spoiled food (fermentation) produce CO_2. The critical difference lies in the VOC profile – mold produces substantial quantities of volatile compounds, causing a dramatic decrease in gas resistance.

B. I^2C Clock Stretching

The SCD30 requires *clock stretching* – a mechanism where the slave device holds the clock line (SCL) low to signal the need for additional processing time. The Raspberry Pi's hardware I^2C controller (BCM2835) has a documented bug [4] and terminates communication prematurely.
The solution is a software I^2C driver via Device Tree Overlay:

```
dtoverlay=i2c-gpio,bus=1,
  i2c_gpio_sda=2,i2c_gpio_scl=3,
  i2c_gpio_delay_us=20
```

C. Software Architecture

The data logger operates asynchronously – InfluxDB communication is decoupled from the sensor reading process to isolate network latencies from the sampling rate. Timestamps are precisely controlled using `time.monotonic()`.

D. Masked Autoencoder

For anomaly detection, we employ a **Masked Autoencoder (MAE)** [5], inspired by self-supervised learning methods such as DINOv3 [6]. Unlike traditional classifiers, the model learns normal physical relationships (e.g., "compressor activates → temperature drops"). Input data segments are randomly masked; the model must reconstruct missing values from context.
When the model can only reconstruct current sensor values with high error, current conditions deviate from the learned normal state – an anomaly is detected.

III. Experiments

A. Datasets

We conducted long-term measurements with a sampling rate of 2 s:

- **Baseline** (empty container): 5,359 data points, ∼3 h
- **Normal** (fresh mandarin): 464,970 data points, >10 days
- **Mold** (moldy orange): 34,808 data points, ∼19 h

B. Results

Table I presents the measured sensor values. Gas resistance emerges as the primary discriminator:

Table I
Comparison of sensor readings across measurement scenarios

Parameter	**Baseline**	**Fresh**	**Mold**
CO_2 (ppm)	513	660	630–640
Gas Resistance	9.8 MΩ	100–500 kΩ	**5–30 kΩ**
Temperature (°C)	13	14	12
Humidity (%)	65	66	64

The results confirm our hypothesis: while CO_2 values remain similar across all scenarios, gas resistance shows a three-order-of-magnitude reduction during mold contamination. This distinctive signature enables reliable classification.

IV. Conclusion

We presented an E-Nose system for food spoilage detection that combines NDIR and MOX sensing with deep learning. Measurements demonstrate that VOC-induced gas resistance is the primary indicator of spoilage. Future work includes expanding training data and deploying the system in real refrigerator environments.

References

[1] Sensirion AG, "Scd30 sensor module: Co2, humidity and temperature sensor," *Datasheet*, 2020. [Online]. Available: https://sensirion.com/products/catalog/SCD30.

[2] Bosch Sensortec, "Bme688: Digital low power gas, pressure, temperature and humidity sensor," *Datasheet*, 2021. [Online]. Available: https://www.bosch-sensortec.com/products/environmental-sensors/gas-sensors/bme688/.

[3] W. Wojnowski, T. Majchrzak, T. Dymerski, J. Gębicki, and J. Namieśnik, "Volatile organic compounds as biomarkers for detection of food spoilage," *TrAC Trends in Analytical Chemistry*, vol. 93, pp. 72–84, 2017.

[4] Raspberry Pi Foundation, "I2c clock stretching bug in bcm2835," *Raspberry Pi Documentation*, 2021. [Online]. Available: https://github.com/raspberrypi/linux/issues/254.

[5] K. He, X. Chen, S. Xie, Y. Li, P. Dollár, and R. Girshick, "Masked autoencoders are scalable vision learners," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 16 000–16 009.

[6] M. Oquab et al., "Dinov3: Towards visual foundation models with self-supervised learning," *arXiv preprint*, 2025.