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iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 20 No. 16 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v20i16.52911

PAPER

Integration of Electronic Nose and Machine Learning for Monitoring Food Spoilage in Storage Systems

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ABSTRACT

The integration of sensor technology and artificial intelligence (AI) is transforming agriculture, particularly in post-harvest management. This study focuses on utilizing an electronic nose (e-nose) system in conjunction with machine learning (ML) models to monitor and detect potato spoilage in storage environments. The e-nose system, equipped with sensitive gas sensors, detects volatile organic compounds (VOCs) emitted by potatoes during different spoilage stages. By analyzing these emissions, the system can identify early signs of spoilage, offering a valuable solution for mitigating post-harvest losses, which remain a significant challenge in the agricultural sector. Through a series of controlled experiments, VOCs were captured and analyzed using a neural network model, classifying the potatoes into three categories: fresh, mildly spoiled, and fully spoiled. The neural network was trained on data from multisensory gas analysis, achieving a high level of classification accuracy. This study demonstrates that the integration of e-nose technology and ML algorithms can effectively monitor potato quality in storage, providing real-time insights to optimize storage conditions, extend shelf life, and reduce wastage.

KEYWORDS

electronic nose (e-nose), machine learning (ML), potato spoilage, volatile organic compounds (VOC), post-harvest loss, gas analysis system

1 INTRODUCTION

Technological advancements are fundamentally reshaping agricultural practices, particularly in food storage systems, where innovation plays a pivotal role in enhancing sustainability and efficiency. Among these innovations, the application of artificial intelligence (AI) and sensor technologies in agriculture, especially in post-harvest management, is emerging as a transformative approach with remarkable potential [1], [2]. While still in its nascent stages, the integration of AI-driven monitoring systems into agricultural storage solutions offers significant opportunities to reduce post-harvest losses and optimize storage conditions [3].

Seilov, S., Abildinov, D., Baydeldinov, M., Nurzhaubayev, A., Zhursinbek, B., Yue, X.G. (2024). Integration of Electronic Nose and Machine Learning for Monitoring Food Spoilage in Storage Systems. *International Journal of Online and Biomedical Engineering (iJOE)*, 20(16), pp. 117–130. https://doi.org/10.3991/ijoe.v20i16.52911

Article submitted 2024-08-09. Revision uploaded 2024-10-03. Final acceptance 2024-10-06.

Post-harvest losses and spoilage of stored products represent a critical challenge to food security and economic stability, particularly for staple crops such as potatoes, which are among the most widely consumed foods globally [3], [4]. Potatoes are highly susceptible to spoilage during storage due to improper environmental conditions. Traditional storage methods lack the precision required to detect early signs of spoilage, leading to substantial financial and resource losses.

Spoilage and storage are intricately linked aspects of food management. Microbial activity is the primary driver of spoilage, making it necessary to continuously adapt storage techniques to mitigate microbial proliferation [5], [6]. Microorganisms, including bacteria, molds, and yeasts, induce changes in the biochemical composition of food products, resulting in the degradation of sensory qualities such as texture, aroma, and appearance. Vegetables, particularly, are vulnerable to spoilage due to microbial activity, enzymatic reactions, and oxidative processes. These processes trigger the production of volatile organic compounds (VOCs) and other by-products that serve as early indicators of spoilage [7], [8].

Conventional methods for assessing food quality, such as microbial testing and chemical analysis, are limited by their inability to provide real-time information on the early stages of spoilage [9], [10]. However, the convergence of advanced sensor technologies—such as electronic noses (e-noses)—and AI, powered by enhanced computing capabilities and cloud-based infrastructure, is enabling real-time monitoring and predictive analytics in agricultural storage environments [11], [12]. These technologies facilitate the early detection of spoilage, improve decision-making processes, and ultimately ensure higher-quality produce for consumers. This approach not only addresses the pressing issue of food waste but also contributes to a more sustainable agricultural ecosystem.

Electronic noses, equipped with sensitive gas sensors, are capable of detecting VOCs emitted by stored crops, allowing for real-time monitoring of produce quality. When integrated with ML algorithms, these systems enable early detection of spoilage, paving the way for enhanced storage conditions and reduced wastage [13], [14]. The novelty of this study lies in its combination of artificial olfaction technology with machine learning (ML) models, specifically tailored to monitor the storage quality of potatoes. Although e-nose systems have been explored across various fields, their application in agricultural storage management—particularly for integration into smart storage solutions—remains underexplored. This study provides novel insights into the potential of ML-driven e-nose systems for detecting spoilage at early stages, thereby improving storage efficiency and prolonging the shelf life of produce [15].

The remainder of this paper is organized as follows: Section 2 presents related works about ML and e-nose technologies in agriculture; Section 3 describes the methodology used for conducting experiments and training the ML model. Section 4 presents the experimental results, and the paper concludes with a discussion of the findings in the final section.

2 RELATED WORKS

2.1 Electronic nose systems in agriculture

Over the last 30 years, the e-nose has recently been one of the most highly used systems in various applications of the agriculture and forestry industries.

Various aroma-sensor technologies have provided solutions that significantly enhanced agricultural and agroforestry production systems globally:

- E-noses have been applied in several commercial agriculturally allied industries, which include agronomy, biochemical processing, botany, plant cell culture, plant cultivar selections, environment monitoring, horticulture, pesticide detection, plant physiology, and plant pathology [16].
- Other uses of forest products included chemotaxonomy, log tracking, wood and paper processing, treatment of forest land, protection of health of forests, and waste management.
- E-noses have been applied to enhance the attributes, quality, uniformity, and consistency of plant-based products, thereby boosting the efficiency and effectiveness of production and manufacturing processes.
- E-nose systems have been designed for remote odor monitoring in and around livestock farms, allowing for improved management and control of odors [17].

The development of e-nose technology regarding improvements in gas-sensor designs, data analysis, pattern recognition algorithms, and material science and systems integration methods resulted in major benefits concerning agriculture and forestry. Perversely, less study continues to be conducted on the identification of animals directly, say, in crops, through the use of e-noses, and much more is required [18].

Integrating e-nose technology with ML has shown to be a highly efficient approach for detecting spoilage in storage settings [19], [20], [21]. An e-nose based on organic field-effect transistors (OFETs) equipped with metalloporphyrin receptors can detect spoilage-related gases at bacterial concentrations as low as 4 × 10^4 CFU g–1, which is 100 times lower than the safety threshold for consumption [19]. ML techniques, such as principal component analysis (PCA) and K-nearest neighbors (KNN), have been employed to analyze the sensor array data from the e-nose, achieving a classification accuracy of 92% in distinguishing different types of food spoilage, including potatoes [21]. In addition, combining commercial gas sensors with an e-nose platform has demonstrated enhanced accuracy and reliability in monitoring real food samples by detecting spoilage indicators such as cadaverine and putrescine [22]. These developments underscore the potential of integrating e-nose technology with ML for the early identification and efficient monitoring of food spoilage in storage systems, enhancing food safety and quality control. However, the application of e-noses in monitoring potato storage conditions, particularly in integration with ML algorithms, has been relatively underexplored.

2.2 Machine learning for spoilage detection

Machine learning has been extensively used for the detection of food spoilage in recent years. Numerous studies have investigated the use of different ML methods for this purpose [23], [24].

A rapid detection method using Fourier-transform infrared (FT-IR) spectroscopy and ML algorithms has been developed to detect microbial spoilage in food samples [25].

Convolutional neural networks and k-means clustering have been used to detect food spoilage by analyzing the color changes in food images [23].

Unsupervised feature learning methods, including stacked restricted Boltzmann machines and autoencoders, have been utilized to classify thin film types, gases, and gas concentrations for detecting meat spoilage [24].

These studies demonstrate the effectiveness of various ML approaches, including deep learning and unsupervised feature learning, in the rapid and accurate detection of food spoilage using different types of sensor data and image analysis.

Despite these advancements, the application of ML to spoilage detection in staple crops such as potatoes remains relatively underexplored. Most of the study focuses on high-value crops or products, leaving a gap in the literature on staple food management.

2.3 Post-harvest loss reduction in potatoes

Post-harvest loss reduction in potatoes is an important strategy for improving food and nutrition security, contributing to several sustainable development goals (SDGs) [26].

According to the studies reviewed:

In the Tiyo district of the Arsi Zone, Ethiopia, the total post-harvest loss of potatoes from harvesting to marketing is estimated to range between 15% and 46%. The losses at various stages were as follows: harvesting (58.9%), sorting (6.2%), cleaning (2.9%), packaging (2.4%), transport from field to storage (3.8%), storage (20.1%), and transport from storage to market (5.7%). The factors contributing to these losses were inadequate harvesting and handling practices, substandard storage facilities, and insect or pest infestations. Factors that significantly influenced potato loss included working family members (increased loss), years of schooling (reduced loss), harvesting based on leaf color change (reduced loss), female respondents (increased storage loss), land size (increased storage loss), and lack of training (increased storage loss) [26]. Compared to in-house and in-basket storage, cold storage had the lowest total loss (4.38%) and respiratory rate and the highest reducing sugar accumulation [27].

To reduce post-harvest losses, the studies recommend interventions such as improving farmers' awareness and skills, demonstrating innovative storage solutions using local materials, promoting appropriate packaging and transport methods, and introducing simple value addition techniques [26].

3 METHODOLOGY

The application of ML technologies necessitates a substantial amount of initial data. To gather this data, experiments were conducted using potatoes stored at room temperature in a humid environment. These conditions were chosen to simulate typical storage scenarios that could affect the quality and longevity of the product. The experiments were performed using a setup equipped with a prototype multisensory gas analytical system, as illustrated in Figure 1.

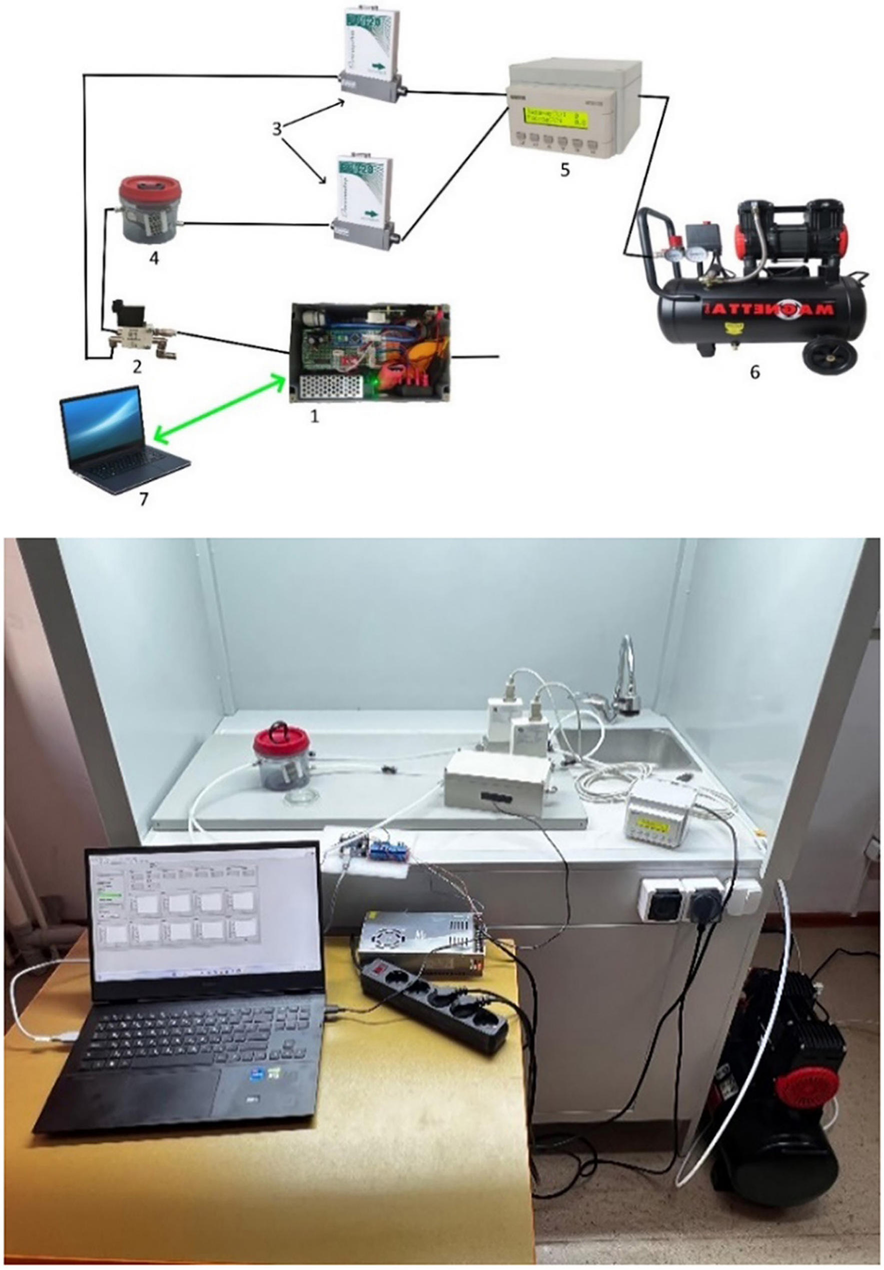


Fig. 1. Laboratory setup

The laboratory setup for this experiment is meticulously designed to assess air quality using an advanced e-nose. Each component plays a crucial role in ensuring accurate and reliable data collection.

1. **Electronic nose:** Equipped with sensitive sensors, this device is the core of our data collection, detecting various gases and odors with precision (see Figure 2).
2. **Flow switch:** This component directs airflow either through the sample container or directly to the e-nose, and its operation is precisely controlled by a microcontroller to ensure accurate measurements.
3. **Gas flow regulator (RRG-20):** These regulators are essential for maintaining a consistent and controlled rate of airflow from the compressor, ensuring that all data collected is under uniform conditions.

4. **Container with a Sample:** This container houses the test sample potatoes, in this case. As air flows through the container, it captures any emitted odors or gases for analysis.
5. **Power supply and control unit:** This unit powers the entire setup and coordinates the operation of various components, including the flow switch and gas flow regulators, ensuring the experiment runs smoothly.
6. **Air compressor:** The air compressor generates a steady stream of air that is carefully regulated and directed through the system, providing the necessary flow for accurate data collection.

This system is designed to detect and analyze various gases emitted by the potatoes during storage. The multisensory approach allows for a comprehensive analysis of the gas composition, which is crucial for developing accurate ML models. The data collected from these experiments will serve as the foundation for training ML algorithms. These algorithms will be used to predict and monitor the quality of stored potatoes, potentially identifying early signs of spoilage or other quality issues. By leveraging this data, the ML models can provide valuable insights and recommendations for optimizing storage conditions and improving the overall quality of the produce.

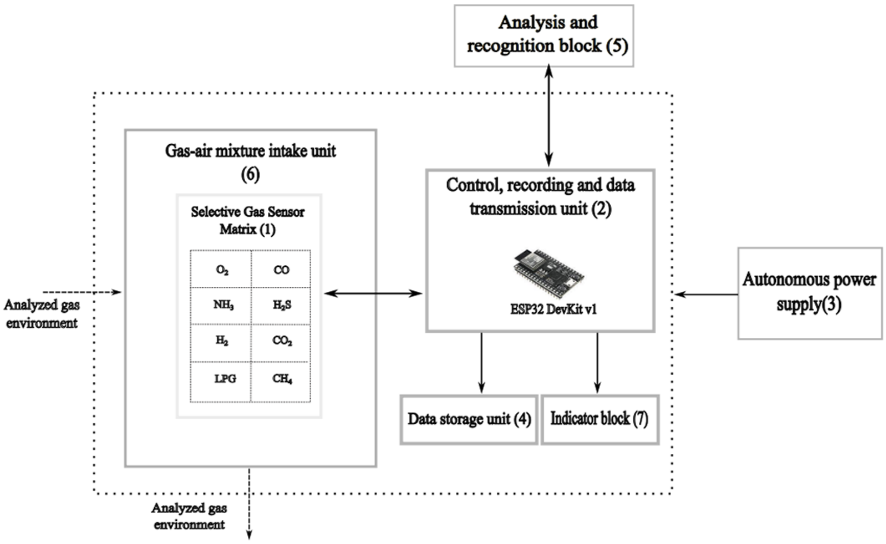


Fig. 2. Schematic diagram of the e-nose system

3.1 Airflow process

The air flow process within the experimental setup is meticulously designed to ensure accurate and consistent analysis of air quality. The procedure can be outlined in the following steps:

1. **Generation of air flow:** The air compressor (6) initiates the process by generating a continuous and steady stream of air. This consistent airflow is essential for reliable data collection and accurate analysis.
2. **Control of air flow rate:** The gas flow regulators (3), specifically the RRG-20 model, precisely control the rate of airflow coming from the compressor. By adjusting the flow rate, these regulators ensure that the air is delivered at a constant and controlled pace.

3. **Pathway division:** The airflow is bifurcated into two distinct paths. One path directs the air through the container with the test sample (4), while the other path bypasses the container and leads directly to the flow switch (2). This division allows for simultaneous testing and comparison.
4. **Flow direction control:** The flow switch (2), managed by a microcontroller, is responsible for directing the airflow. It can either channel the air through the container with the sample or directly towards the e-nose (1). This control is crucial for alternating between sampling and baseline measurements.
5. **Data collection:** The e-nose (1) is equipped with sensors that detect and analyze any gases or odors present in the airflow. This device captures real-time data on the chemical composition of the air, which is vital for identifying specific odors or gases.
6. **Data transmission and processing:** Once the e-nose (1) has collected the data, it is transmitted to a computer (7). This computer is responsible for storing the data and performing further analysis. The data processing includes interpreting the detected gases or odors and generating meaningful results for the experiment.

3.2 Experimental procedure

To ensure consistent and reliable data collection, the experiments were meticulously planned and executed according to the following procedure:

- **Duration:** Each experimental session was conducted over a span of 75 minutes. This duration was divided into three distinct phases to ensure comprehensive data collection and accurate results:
- **30 minutes:** The first phase involved running clean air through the e-nose. This step was essential for establishing baseline readings and ensuring that the sensors were properly calibrated before introducing any test samples.
- **15 minutes:** During this phase, the airflow was directed through the container with the potato sample. This period allowed for the detection and analysis of any odors or gases emitted by the sample, providing data on the specific characteristics of the test material.
- **30 minutes:** The final phase involved resuming clean air flow through the e-nose. This phase was crucial for verifying that the sensor readings returned to baseline levels and to assess any residual effects from the test sample.
- **Timeline:** The series of experiments was conducted over a specified period. The experimental sessions commenced on May 1, 2024, and concluded on June 5, 2024. This timeline allowed for a thorough investigation of the air quality and ensured that sufficient data was collected for analysis.

3.3 Training neural networks

Neural network training was performed using utilities from the Matlab package [22]. The process involved the following steps:

- **Data collection:** All experimental data pertaining to the potatoes were aggregated into a single dataset file. This file was meticulously compiled to ensure that it contained comprehensive data from all experiments conducted. Each entry in the dataset was carefully recorded to reflect the conditions and results of the experiments.

- **Data labeling:** An additional column labeled 'Label' was introduced to categorize the data for the classification task. The labels were assigned as follows: **F**-Fresh: Data entries corresponding to fresh potatoes, representing the baseline state of the sample; **M**-Mild: Data entries associated with potatoes that exhibited mild spoilage, indicating an early stage of deterioration; **S**-Spoiled: Data entries for potatoes that were identified as spoiled, reflecting significant spoilage and degradation.
- **Training process:** The labeled dataset was used to train the neural networks. The training involved using Matlab's built-in utilities to process the data, tune the network parameters, and optimize the model for accurate classification. The neural networks were configured to learn from the patterns in the data, with the goal of effectively distinguishing between the different states of the potatoes based on the collected features.
- **Visualization:** The dataset and its labeling provide a visual representation of the data distribution and labeling scheme. This visualization helps in understanding the data organization and the classification categories used during the training process.

The Matlab script was developed to automate the process of training a neural network (see Figure 3).

```
     % Load the dataset for experiment
     filename = "Data for experiment 050224_.csv";
     tbl = readtable(filename, 'TextType', 'String');
     % Convert the 'Label' column to categorical for classification
     labelName = "Label";
     tbl = convertvars(tbl, labelName, 'categorical');
     % Display the first few rows of the table
     head(tbl)
     % Determine the number of observations
     numObservations = size(tbl, 1);
     numObservations = 5901;
     % Split the data into training, validation, and test sets
     numObservationsTrain = floor(0.7 * numObservations);
     numObservationsValidation = floor(0.15 * numObservations);
     numObservationsTest  =  numObservations  -  numObservationsTrain  -
numObservationsValidation;
     % Randomly permute the indices for the split
     idx = randperm(numObservations);
     idxTrain = idx(1:numObservationsTrain);
     idxValidation=idx(numObservationsTrain+1:numObservationsTrain+nu
mObservationsValidation);
     idxTest=idx(numObservationsTrain+numObservationsValidation+1:end
);
     % Create the datasets for training, validation, and testing
     tblTrain = tbl(idxTrain, :);
     tblValidation = tbl(idxValidation, :);
     tblTest = tbl(idxTest, :);
     % Set up the neural network architecture
     numFeatures = size(tbl, 2) - 1;
     numClasses = numel(classNames);
     layers = [
     featureInputLayer(numFeatures,'Normalization',      'zscore')
     fullyConnectedLayer(50)
   ];
```

Fig. 3. Matlab script for training neural network

This script performs several key functions:

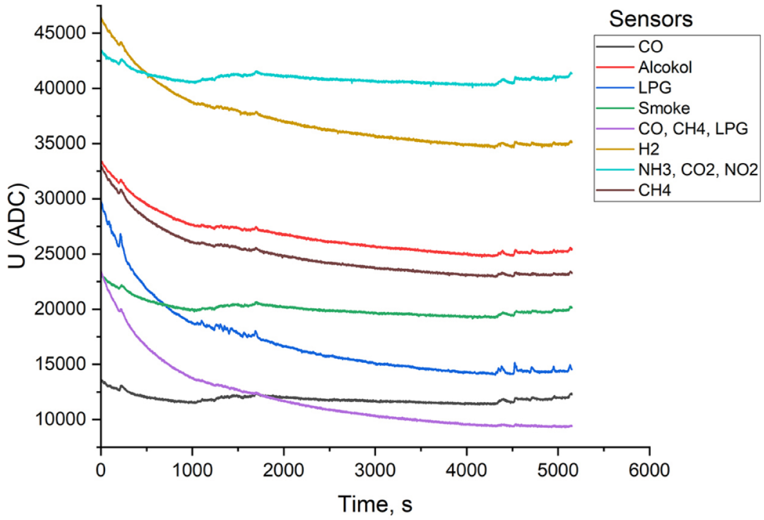
1. **Data loading:** The script begins by loading the dataset required for training. This involves reading data from various sources, such as CSV files, databases, or other formats, and organizing it into a format suitable for neural network training.
2. **Configuration settings:** After loading the data, the script sets up the required configurations for the neural network. This involves specifying the network architecture (e.g., number of layers and neurons per layer), adjusting hyperparameters (e.g., learning rate, batch size, and number of epochs), and initializing the weights.
3. **Data preprocessing:** Before training, the script preprocesses the data. This step may involve normalizing or standardizing the data, handling missing values, and splitting the data into training, validation, and test sets.
4. **Training the neural network:** With the data prepared and the network configured, the script proceeds to train the neural network. This involves feeding the training data into the network, performing forward and backward propagation, and updating the weights based on the loss function. The script also monitors the training process, recording metrics such as loss and accuracy over each epoch.
5. **Evaluation and results:** After training, the script evaluates the performance of the neural network on the validation and test sets. It generates various performance metrics, including accuracy, precision, recall, and F1-score. The outcomes are displayed using a confusion matrix, as illustrated in Figure 5. This matrix offers a detailed summary of the network's performance, presenting the counts of true positives, true negatives, false positives, and false negatives.
6. **Saving the model:** Finally, the script saves the trained neural network model to a file, allowing it to be loaded and used for predictions in the future. This step ensures that the trained model can be reused without needing to retrain it from scratch.

4 EXPERIMENTAL RESULTS

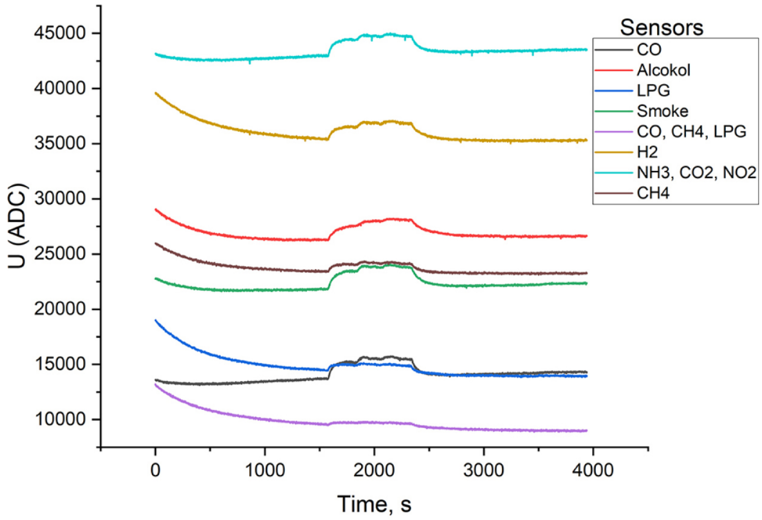
The experiments conducted aimed to test the efficacy of the e-nose system in detecting spoilage in stored potatoes. The experiments involved monitoring the release of gases from potatoes stored under different conditions using a multisensory gas analysis system. This system, integrated with ML models, analyzed the gas emissions to classify the potatoes as fresh, mildly spoiled, or fully spoiled.

Experiments were conducted over a series of days, with the following procedure repeated during each session. These controlled sessions allowed for the detection and analysis of VOCs emitted by the potatoes as they underwent spoilage. The e-nose system captured VOCs emitted during spoilage, providing a rich dataset of gas concentrations over time as shown in Figure 4. The gases detected included indicators of microbial activity such as ammonia (NH_3), sulfur compounds, and other metabolites linked to spoilage.

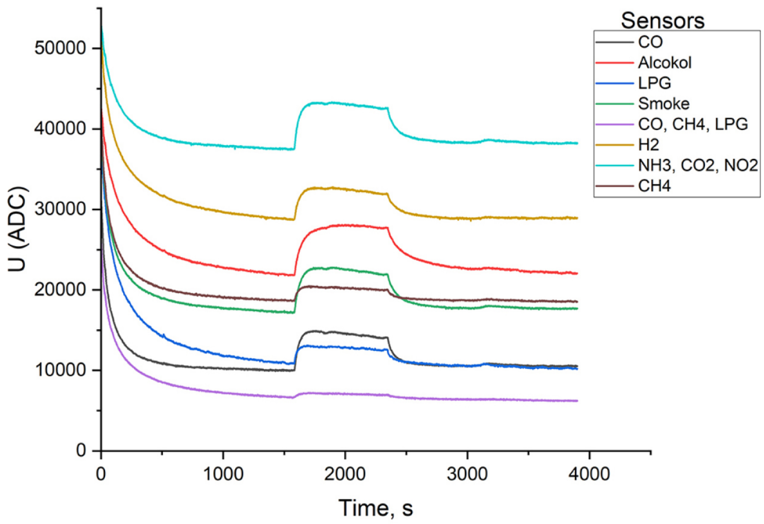
The sensors exhibited a clear distinction between the different spoilage stages. For example, fresh potatoes emitted minimal amounts of spoilage-related gases, while mildly spoiled potatoes exhibited noticeable increases in ammonia and sulfur compounds. Fully spoiled potatoes showed significantly higher emissions across all spoilage indicators.



May 1, 2024, wet potatoes 30 min clean air, 15 min sample, 30 min clean air



May 5, 2024, wet potatoes 30 min clean air, 15 min sample, 30 min clean air



May 7, 2024, wet potatoes 30 min clean air, 15 min sample, 30 min clean air

Fig. 4. Results of experiments with wet potatoes

A neural network was trained using experimental data to classify potatoes into three categories: fresh (F), mild spoilage (M), and spoiled (S). The model was trained and validated using the split dataset from the experimental sessions, achieving high classification accuracy.

The confusion matrix (see Figure 5) summarizes the performance of the ML model. The model correctly classified most of the samples, with a strong distinction between fresh, mildly spoiled, and fully spoiled potatoes.

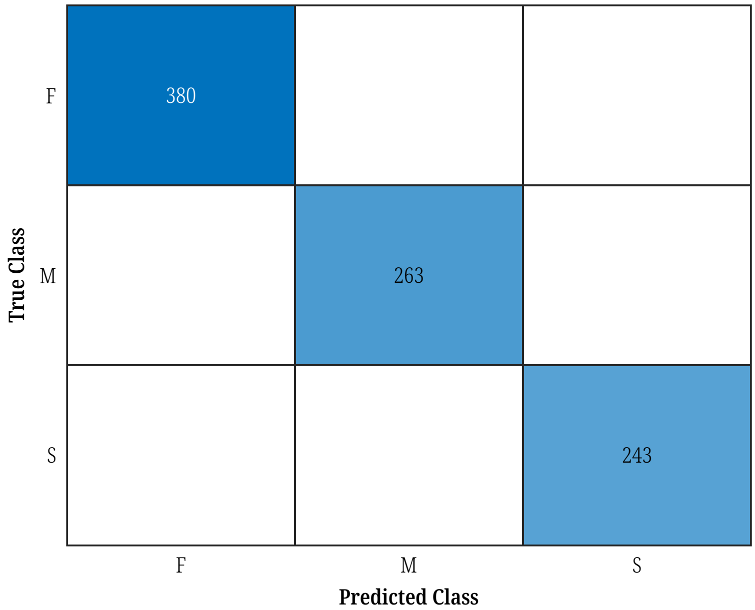


Fig. 5. Confusion matrix showing the performance of the neural network

As demonstrated in the matrix, the model accurately detected the fresh and spoiled states of the potatoes, though there were some misclassifications between mild spoilage and fully spoiled samples, likely due to overlapping VOC emissions in these stages.

5 CONCLUSIONS

This study presents a novel approach to integrating ML with e-nose technology to detect spoilage in stored potatoes. By utilizing multisensory gas analysis, this study demonstrates that the system can successfully classify potatoes into different spoilage stages (fresh, mildly spoiled, and fully spoiled) based on VOCs emissions. The experimental setup, combining sensitive gas sensors with ML algorithms, achieved high accuracy in detecting early spoilage indicators, which could be critical for optimizing storage conditions and reducing post-harvest losses.

The neural network model demonstrated robust performance in classifying spoilage states, as validated by the confusion matrix. Although there were minor misclassifications between mildly spoiled and fully spoiled samples, the results indicate that technology holds promise for real-world implementation in smart agricultural storage systems.

As part of our future developments, we plan to enhance the e-nose system by incorporating trained neural networks implemented on field-programmable gate arrays (FPGAs). FPGAs offer parallel data processing capabilities, which enable efficient real-time signal generation that can indicate specific environmental conditions or plant health factors. This shift will address several challenges, including reducing computational latency and improving energy efficiency compared to traditional methods like GPUs or cloud-based processing.

The neural network training will be conducted on stationary devices using standard tools such as Jupyter and Matlab. Once trained, the networks will be implemented on FPGAs, allowing for faster processing directly at the device level. While FPGAs present a higher entry barrier due to the need for both hardware design and neural network development skills, they offer significant advantages in flexibility, scalability, and energy efficiency. This approach is expected to make the e-nose system more autonomous and capable of performing complex classification tasks in real-time, thereby enhancing its application for diverse agricultural monitoring and spoilage detection tasks.

6 ACKNOWLEDGMENTS

This work was carried out with financial support from the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant AP19680157).

7 REFERENCES

[1] R. C. de Oliveira and R. D. de S. e Silva, "Artificial intelligence in agriculture: Benefits, challenges, and trends," *Applied Sciences*, vol. 13, no. 13, p. 7405, 2023. https://doi.org/10.3390/app13137405

[2] A. Singh *et al.*, "Recent advancement in postharvest loss mitigation and quality management of fruits and vegetables using machine learning frameworks," *J. Food Qual.*, vol. 2022, no. 1, pp. 1–9, 2022. https://doi.org/10.1155/2022/6447282

[3] D. M. Rodrigues *et al.*, "Applying remote sensing, sensors, and computational techniques to sustainable agriculture: From grain production to post-harvest," *Agriculture*, vol. 14, no. 1, p. 161, 2024. https://doi.org/10.3390/agriculture14010161

[4] A. K. Jaiswal, B. Singh, A. Mehta, and M. Lal, "Post-harvest losses in potatoes from farm to fork," *Potato Res.*, vol. 66, pp. 51–66, 2023. https://doi.org/10.1007/s11540-022-09571-y

[5] L. Gram, L. Ravn, M. Rasch, J. B. Bruhn, A. B. Christensen, and M. Givskov, "Food spoilage—interactions between food spoilage bacteria," *Int. J. Food Microbiol.*, vol. 78, nos. 1–2, pp. 79–97, 2002. https://doi.org/10.1016/S0168-1605(02)00233-7

[6] A. Lianou, E. Z. Panagou, and G.-J. E. Nychas, "1 – Microbiological spoilage of foods and beverages," in *The Stability and Shelf Life of Food* (Second Edition), Woodhead Publishing Series in Food Science, Technology and Nutrition, 2016, pp. 3–42. https://doi.org/10.1016/B978-0-08-100435-7.00001-0

[7] L. Kuuliala, N. Jain, B. De Baets, and F. Devlieghere, "Identifying potential volatile spoilage indicators in shredded carrot using SIFT-MS," in *Dynamic Flavor: Capturing Aroma Using Real-Time Mass Spectrometry*, ACS Symposium Series, American Chemical Society, vol. 1402, 2021, ch. 9, pp. 107–122. https://doi.org/10.1021/bk-2021-1402.ch009

[8] A. A. Abdullah *et al.*, "Analysis of volatile metabolites emitted by various species to reveal their roles in chemical ecology and healthcare," in *2015 2nd International Conference on Biomedical Engineering (ICoBE)*, 2015, pp. 1–6. https://doi.org/10.1109/ICoBE.2015.7235881

[9] M. Efenberger-Szmechtyk, A. Nowak, and D. Kregiel, "Implementation of chemometrics in quality evaluation of food and beverages," *Crit. Rev. Food Sci. Nutr.*, vol. 58, no. 10, pp. 1747–1766, 2018. https://doi.org/10.1080/10408398.2016.1276883

[10] W. Bernard Betts, "The potential of dielectrophoresis for the real-time detection of micro-organisms in foods," *Trends Food Sci. Technol.*, vol. 6, no. 2, pp. 51–58, 1995. https://doi.org/10.1016/S0924-2244(00)88943-8

[11] A. V. Agrawal *et al.*, "Synergizing artificial intelligence, 5G, and cloud computing for efficient energy conversion using agricultural waste," in *Sustainable Science and Intelligent Technologies for Societal Development*, B. Mishra, Ed., 2024, pp. 475–497. https://doi.org/10.4018/979-8-3693-1186-8.ch026

[12] T. Rajesh, K. T. Kumar, M. M. Balan, and M. S. Sidhartha, "E-agriculture based on AI and IOT," *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, vol. 7, no. II, pp. 343–347, 2019. https://doi.org/10.22214/ijraset.2019.2038

[13] Y. Chang, H. Qu, X. Duan, L. Mu, and M. A. Reed, "VOC detection using multimode E-nose composed of bulk acoustic wave resonator and silicon nanowire field effect transistor array," in *2016 IEEE SENSORS*, 2016, pp. 1–3. https://doi.org/10.1109/ICSENS.2016.7808606

[14] J. C. Rodriguez Gamboa, E. S. Albarracin E, A. J. da Silva, L. L. de Andrade Lima, and T. A. E. Ferreira, "Wine quality rapid detection using a compact electronic nose system: Application focused on spoilage thresholds by acetic acid," *LWT*, vol. 108, pp. 377–384, 2019. https://doi.org/10.1016/j.lwt.2019.03.074

[15] H. Wang, Z. Hu, F. Long, C. Guo, Y. Yuan, and T. Yue, "Early detection of *Zygosaccharomyces rouxii*—spawned spoilage in apple juice by electronic nose combined with chemometrics," *Int. J. Food Microbiol.*, vol. 217, pp. 68–78, 2016. https://doi.org/10.1016/j.ijfoodmicro.2015.10.010

[16] A. D. Wilson, "Diverse applications of electronic-nose technologies in agriculture and forestry," *Sensors*, vol. 13, no. 2, pp. 2295–2348, 2013. https://doi.org/10.3390/s130202295

[17] L. Pan and S. X. Yang, "An electronic nose network system for online monitoring of livestock farm odors," *IEEE/ASME Transactions on Mechatronics*, vol. 14, no. 3, pp. 371–376, 2009. https://doi.org/10.1109/TMECH.2009.2012850

[18] M. P. A. F. Kiki, S. A. R. M. Ahouandjinou, K. M. Assogba, and T. Sutikno, "Bibliometric analysis and survey on electronic nose used in agriculture," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 2, pp. 1369–1381, 2024. https://doi.org/10.11591/ijece.v14i2.pp1369-1381

[19] A. Khorramifar, M. Rasekh, H. Karami, J. Lozano, M. Gancarz, and E. Łazuka, "Determining the shelf life and quality changes of potatoes (Solanum tuberosum) during storage using electronic nose and machine learning," *PLoS One*, vol. 18, no. 4, p. e0284612, 2023. https://doi.org/10.1371/journal.pone.0284612

[20] D. S. Anisimov, A. A. Abramov, V. P. Gaidarzhi, D. S. Kaplun, E. V Agina, and S. A. Ponomarenko, "Food freshness measurements and product distinguishing by a portable electronic nose based on organic field-effect transistors," *ACS Omega*, vol. 8, no. 5, pp. 4649–4654, 2023. https://doi.org/10.1021/acsomega.2c06386

[21] Z. Ye, Y. Liu, and Q. Li, "Recent progress in smart electronic nose technologies enabled with machine learning methods," *Sensors*, vol. 21, no. 22, p. 7620, 2021. https://doi.org/10.3390/s21227620

[22] M. Gancarz, J. Wawrzyniak, M. Gawrysiak-Witulska, D. Wiącek, A. Nawrocka, and R. Rusinek, "Electronic nose with polymer-composite sensors for monitoring fungal deterioration of stored rapeseed," *Int. Agrophys.*, vol. 31, pp. 317–325, 2017. https://doi.org/10.1515/intag-2016-0064

[23] R. K. Megalingam, G. S. Sree, G. M. Reddy, I. R. S. Krishna, and L. U. Suriya, "Food spoilage detection using convolutional neural networks and k means clustering," in *2019 3rd International Conference on Recent Developments in Control, Automation & Power Engineering (RDCAPE)*, 2019, pp. 488–493. https://doi.org/10.1109/RDCAPE47089.2019.8979114
[24] M. Längkvist, S. Coradeschi, A. Loutfi, and J. B. B. Rayappan, "Fast classification of meat spoilage markers using nanostructured ZnO thin films and unsupervised feature learning," *Sensors*, vol. 13, no. 2, pp. 1578–1592, 2013. https://doi.org/10.3390/s130201578
[25] J. J. Rowland, D. I. Broadhurst, D. I. Ellis, and R. Goodacre, "Rapid detection method for microbial spoilage using FT-IR and machine learning," in *Rapid Methods for Food and Feed Quality Determination*, A. van Amerongen, D. Barug, and M. Lauwaars, Eds., Wageningen Academic Publishers, 2005, pp. 73–81.
[26] S. M. Yimenu *et al.*, "Postharvest practices and loss determinants for interventions among smallholder potato farmers in Tiyo District, Arsi Zone, Ethiopia," *African Journal of Food, Agriculture, Nutrition and Development*, vol. 24, no. 4, pp. 26202–26228, 2024. https://doi.org/10.18697/ajfand.129.23595
[27] S. Khanal and K. Bhattarai, "Study on post harvest losses in potato in different storage conditions," *Journal of Food Science and Technology Nepal*, vol. 12, no. 12, pp. 14–19, 2020. https://doi.org/10.3126/jfstn.v12i12.25298

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