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Automated Detection of Porcine Gelatin Using Deep Learning-Based E-Nose to Support Halal Authentication

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ABSTRACT Authenticating gelatin sources is crucial for consumers, particularly those with dietary restrictions or religious concerns, such as avoiding pork-derived ingredients. Porcine gelatin, widely used in food and pharmaceuticals products, poses considerable challenges for authentication due to its prevalence and the difficulty in detecting it, particularly in processed products. As the demand for rapid and reliable food authentication methods grows, the need for efficient and scalable technologies becomes increasingly critical. Notably, the integration of advanced tools, such as deep learning (DL) can enhance the accuracy and efficiency of detecting and classifying gelatin sources. This study developed and evaluated an integrated electronic nose (e-nose) system with a Recurrent Neural Network (RNN) to detect and classify gelatin types based on their sources. The e-nose system utilized an array of gas sensors to capture the unique volatile organic compounds (VOCs) associated with each gelatin type, which were subsequently classified by the RNN. The e-nose system incorporates seven gas sensor modules designed to identify the unique chemical signatures of porcine, bovine, and fish gelatin. The classification performance of the integrated 7-module e-nose system showed promising results based on time points after sample preparation, with accuracy, sensitivity, and AUC of 96.3%, 96.6%, and 98.2% at the 0-hour point, respectively, rising to 99.1% for all three metrics at 2-hour point. The sensitivity of the system also showed an increase over time for single gelatin samples, from 100%, 97.8%, and 91.9% to 98.6%, 99.3%, and 99.3% for pig-derived, cow-derived, and fish gelatin, respectively. For mixed gelatin samples, the system maintained high accuracy, sensitivity, and AUC at 98.2%, 97.9%, and 98.1%, respectively. The results demonstrate that the integrated e-nose system effectively differentiates between gelatin types with high performance in both single and mixed samples. This highlights its potential as a robust tool for gelatin authentication which pave the way to more efficient and reliable methods for ensuring halal compliance.

INDEX TERMS e-nose, halal authentication, integrated e-nose, porcine gelatin detection, RNN

I. INTRODUCTION

The exponential growth of the global halal market reached $2.1 trillion in 2020 and is projected to surge to $9.17 trillion by 2025 [1]. The diverse range of food and beverage products available in the market—characterized by different compositions, forms, flavors, and preparation methods—poses challenges for consumer to ascertain a product's halal status, especially in the absence of clear authentication on the packaging or similar indicators [2]. This complexity is further exacerbated by the potential presence of pork-derived ingredients, such as porcine gelatin, which may undergo extensive processing in their composition or methodologies which further make detection difficult. In accordance with certain religious beliefs, it is strictly prohibited to consume pork-derived ingredients in various food products, even in the smallest portion [3], [4]. This underscores the critical importance of supporting halal authentication efforts, including rigorously research-based testing methodologies.

Gelatin is a colorless protein derived from collagen found in the connective tissues of animal bones and skins [5]. It is widely used across various industries, including the food industry as a thickener, emulsifier, plasticizer and in the pharmaceutical industry as sugar-coating tablets and pills, and vitamins encapsulating [6], [7], [8]. Despite its widespread applications, gelatin remains a controversial ingredient, particularly in the context of Halal food production [9]. The majority of gelatin is derived from pig and cattle bones and hides [10]. Although fish-derived gelatin is available, it represents only a small ratio compared to that sourced from pigs and cattle. It is found that in Europe, approximately 80% of gelatin is sourced from porcine sources [11], while only 1.5% is derived from fish [12] and the remaining gelatin is sourced from cattle. Animal-derived components such as gelatin can be identified through their lipid, protein, or DNA profiles, with various analytical techniques employed for this purpose. Among the prominent techniques are protein-based assays, DNA-based methods, chromatography, spectroscopy, and SDS-PAGE. Each of these methods has distinct strengths and weaknesses; for instance, while protein-based methods offer specificity in detecting pork proteins, they may not be as sensitive as DNA-based techniques, which can detect even minute quantities of genetic material [13]. Chromatography and spectroscopy provide robust quantitative analyses but often require complex instrumentation and extensive sample preparation [14].

Despite advancements in detection methodologies, a trade-off remains between accuracy and practicality. High-accuracy detection techniques often necessitate sophisticated instrumentation and meticulous preparation which results in extended processing times and heightened costs. In contrast, simpler methods, while rapid and less reliant on advanced equipment, frequently yield lower accuracy [15]. Thus, the imperative for a balance between accuracy, cost, equipment complexity, and processing time underscores the urgent need for innovative methodological approaches that effectively address these challenges.

Another method for detecting the presence of animal-derived components is through the analysis of their volatile organic compounds (VOCs) [16]. VOCs, including aldehydes, hydrocarbons, organic acids, and alcohols, and others play a significant role in determining the aroma of a substance [17]. The presence of these compounds, which can be emitted from both single animal types and mixtures, is crucial for identification and analysis. The electronic nose (e-nose) has emerged as a promising alternative for detecting and differentiating odor patterns, particularly in food authentication and adulteration [18], [19]. The e-nose is an odor analyzer that consists of a gas sensor array designed to mimic an artificial olfactory system, enabling the analysis of odors from both individual compounds and mixtures. It can be applied to various samples, including foods with distinct odors [20]. One of e-nose primary strengths is the ability to provide rapid and real-time analysis that enables immediate results [21]. This is particularly valuable in high-throughput settings where quick decision-making is essential. Compared to the aforementioned methods, which often entail lengthy preparation and processing times, the e-nose offers a more efficient alternative by detecting a wide array of volatile compounds emitted by gelatin products [22]. This enables effective identification of specific sources—fish, bovine, or porcine—by analyzing their unique olfactory signatures. Moreover, e-nose is generally more cost-effective, as it requires less sophisticated laboratory infrastructure compared to methods like chromatography, which necessitate expensive equipment and trained personnel [21]. While the e-nose offers significant advantages in detecting and classifying volatile compounds, it is not without limitations. A primary concern is its sensitivity where the e-nose's ability to detect subtle variations in compound concentrations can lead to inconsistent results if not properly managed. Moreover, the data generated by e-noses require advanced processing techniques for accurate interpretation of complex signal patterns. To address this challenge, the e-nose needs suitable learning algorithms to extract and interpret the intricate patterns detected by its sensors, which is essential for effectively classifying or differentiating between various gelatin sources. Integrating signal data from multiple e-nose systems with machine learning (ML) and deep learning (DL) techniques offers significant potential to enhance the capabilities of detection systems. For instance, as demonstrated in [23], the use of four different supervised learning methods to detect the origin of meat floss revealed that e-nose systems show promising results in food authenticity testing. Similarly, [24] employed seven ML models integrated with an e-nose to detect honey adulteration, successfully developing a methodology capable of identifying adulterated honey, thereby proving its potential application in honey quality control. Compared to traditional ML models, DL can automatically learn complex features from raw data, handle non-linear relationships, and adapt to diverse data patterns [25]. This makes DL particularly well-suited for tasks involving intricate VOC profiles generated by e-nose systems. Therefore, investigating the effectiveness of DL in this context is crucial to fully leveraging its capabilities for advancing e-nose-based detection systems. Among DL models, RNNs are particularly well-suited for processing sequential data, as they can effectively track temporal dependencies in the signals collected from the e-nose [26]. This integration not only improves detection performance but also addresses the critical need for Halal authentication in food products which ensures compliance with dietary regulations.

In this study, we integrated multiple e-nose modules with a DL model to detect the presence of porcine gelatin and classify various gelatin sources. The model's performance was evaluated for distinguishing between porcine, bovine, and fish gelatin. To comprehensively assess the model, we also examined the effectiveness of each module and the impact of two time points: immediately after preparation (0 hours) and 2 hours post-preparation. The gelatins analyzed in this study included both pure and mixed gelatin with designated concentrations.

II. RELATED WORKS

This section presents an analysis of prior research on gelatin authentication methods, highlighting the limitations of these techniques. Additionally, it explores the application of e-nose-based food authentication methods across a wide range of food types. Furthermore, the use of Recurrent Neural Networks (RNN) and the specific evaluation metrics employed in this study are discussed in detail.

A. GELATIN AUTHENTICATION TECHNIQUES

To date, numerous methods for gelatin authentication have been developed, including immunological techniques such as enzyme-linked immunosorbent assay (ELISA) [27], [28], DNA-based methods like Polymerase Chain Reaction (PCR) [29], PCR-Restriction Fragment Length Polymorphism (PCR-RFLP) [30], and real-time PCR (qPCR) [31]. Additionally, sensor-based and spectroscopic techniques have also been utilized [32], [33]. These methods offer high sensitivity and specificity, enabling precise detection of adulterants like porcine gelatin in food products.

However, each of these techniques comes with its limitations. Immunological methods such as ELISA, while effective, require extensive sample preparation and can be time-consuming. DNA-based methods like PCR and qPCR, though highly accurate, often demand sophisticated equipment and trained personnel, limiting their accessibility for routine food testing. Sensor-based and spectroscopic techniques, while faster and non-destructive, generally offer lower sensitivity and specificity compared to their immunological and DNA-based counterparts. These limitations underscore the need for more integrated and versatile approaches to improve the efficiency and accuracy of food authentication processes.

In this regard, the e-nose presents itself as a promising alternative, offering a novel approach to improving detection methodologies. The primary strengths include the ability to provide rapid and real-time analysis that enables immediate results. Moreover, the e-nose is generally more cost-effective, as it requires less sophisticated laboratory infrastructure compared to methods like chromatography, which necessitate expensive equipment and trained personnel. TABLE 1 summarizes the application of the E-nose in food authenticity evaluation in recent years.

Han et al. proposed a cost-effective electronic nose (e-nose) technology that integrates colorimetric sensors with Fourier Transform Near-Infrared (FT-NIR) spectroscopy [34]. Their research demonstrated the successful application of the Extreme Learning Machine (ELM) model in identifying beef adulteration with duck meat and predicting the extent of this adulteration. Chen et al. and Oates et al. utilized a Metal Oxide Semiconductor (MOS) e-nose in conjunction with other detection methods to analyze various non-mixed meat products [35], [36]. Their approach involved evaluating response data from analytical instruments to assess meat authenticity and differentiate between distinct types of meat. Roy et al. employed e-nose technology to detect adulteration in liquid foods, specifically focusing on olive oil [37]. Zarezadeh et al. introduced a novel fusion detection method that combines e-nose technology with an ultrasonic detection system to evaluate the authenticity of extra virgin olive oil [38]. Their findings indicated that the characterization capabilities of certain ultrasound data may surpass those of olfactory data; however, the integration of both methodologies could yield superior evaluation results. It is noteworthy that both the transmitted signal and residual vibration can interfere with the echo signal, potentially distorting ultrasound data. Therefore, further investigation is warranted to ascertain the feasibility and effectiveness of combining e-nose technology with ultrasonic detection in the food sector.

TABLE 1
E-nose applications in food authentication

Sample	Application	Analysis method	Ref.
Duck and Beef	Qualitative and quantitative detection of beef adulterated with duck.	SNV, MSC, PCA, ELM	[34]
Chicken	Quality evaluation and adulteration identification of beijing-you chicken.	CDA	[35]
Multiple types of meat	Detection of different foodstuffs.	PCA, DA, RF	[36]
Soybean Oil	Detection of soybean oil adulteration in cow ghee (clarified milk fat)	PCA, SIMCA, DFA	[37]
Olive Oil	Olive oil classification and fraud detection using e-nose and ultrasonic system	PCA, GBC, SVM, ANN	[38]
Raw milk	Rapid detection of acid neutralizers adulteration in raw milk	PCA, PLS-DA, RF, MLP	[39]
Pure/industrial fruit juice	Preliminary study non-destructive sorting techniques for pepper (capsicum annuum l.) using odor parameter	PCR, ANN	[40]

In the context of dairy product adulteration detection, Tian et al. conducted three authenticity evaluation studies wherein they simulated adulteration by introducing neutralizing acid dopants (e.g., NaOH, NaSCN) and vegetable oils (e.g., corn oil, palm oil) into raw milk [39]. The adulterated samples were subsequently analyzed using the Hercules II e-nose. Rasekh et al. executed two separate studies, successfully combining e-nose detection technology with artificial neural network algorithms to identify natural and industrial fruit juices, thereby facilitating the detection of adulteration in these products [40].

Overall, e-noses have consistently demonstrated their effectiveness as reliable tools for assessing food authenticity. Their capacity to analyze and detect specific volatile compounds allows for the identification of adulteration and contamination in a variety of food products. Moreover, by improving the accuracy and speed of authenticity assessments, e-noses contribute significantly to the credibility and reputation of the food industry. As the demand for transparency and quality in food production increases, the use of e-nose technology represents a crucial advancement in upholding industry standards and fostering consumer trust.

However, despite its widespread application, the e-nose still has limitations, particularly in accurately processing complex data patterns over time and differentiating between closely related compounds, as it produces dynamic signal data that can vary with environmental conditions. Although Recurrent Neural Networks (RNNs) are well-suited to model sequential data and capture temporal dependencies, their application in e-nose technology remains limited and underexplored. Therefore, integrating the e-nose with RNNs has potential to enhance the system's ability to handle fluctuating and complex VOC signals which can improve performance in VOC classification.

B. RECURRENT NEURAL NETWORK (RNN)

Recurrent Neural Networks (RNNs) have become a key tool in handling sequential data and have become particularly suitable for applications involving sensor-based data. Unlike traditional feedforward neural networks, which assume that inputs are independent of each other, RNNs introduce recurrent connections that allow the network to retain information from previous time steps as shown in FIGURE 1.

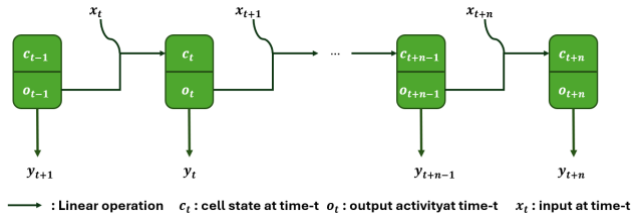

FIGURE 1. RNN architecture

The model's output activity or neuronal activity o_t at time-t is determinde by the recurrent connections $V_r$and the input $x_t$through the connections V_x. The output of the system is extracted through the connections represented by V_y defined as follows (Eq. (1) to Eq. (4)):

$$c_t = V_r o_{t-1} + V_x x_t + a_o, \quad (1)$$

$$o_t = f(c_t), \quad (2)$$

$$y_t = V_y o_t + a_y. \quad (3)$$

Output activity of o_t, can be expanded in time as follows.

$$o_t = f(V_r o_{t-1} + V_x x_t + a_o),\ t = 1, \dots, n \quad (4)$$

From Eq. (4), it is evident that the neuron at time-t (denoted as o_t) receives inputs from the previous layer's o_{t-1} at time $(t-1)$, along with an additional input from outside the recurrent network, x_t. This system enables the network to learn temporal dependencies, which are crucial in tasks involving sequential data such as signals from electronic noses (e-noses). This model generates sequences of sensor readings that reflect the properties of volatile compounds therefore ideal for classification problems like gelatin detection.

Previous studies have demonstrated the effectiveness of RNNs in tasks related to food safety and quality control. For instance, Nagamalla et al. used RNNs to classify time-series data from food samples and achieved high accuracy in detecting adulterated products. Similarly, RNNs are employed to model sensor data from e-nose achieving promising results [41]. However, these works primarily focus on general food safety applications and do not specifically address the challenges of detecting porcine gelatin or pig derivatives using sensor-based modules. In the context of this study, the RNN is used to classify gelatin samples based on signals collected from sensor-based modules. These signals are numerical data that represent the presence of various compounds, including pig-derived or porcine gelatin. The recurrent nature of the RNN allows it to model the temporal structure of the signals, which is crucial for detecting subtle differences in the sensor readings over time.

C. EVALUATION METRICS

In this study, the performance of the Recurrent Neural Network (RNN) in detecting porcine gelatin for halal authentication is evaluated using three key metrics: accuracy, sensitivity, and AUC. These metrics are critical due to the significant implications of misclassification for Halal food compliance.

Accuracy as formulated in Eq. (5) measures the proportion of correct predictions (true positives and true negatives) out of all predictions, serving as an indicator of the model's effectiveness in classifying samples from different sources. High accuracy is essential for reliably identifying all gelatin sources and supporting halal authentication. Sensitivity (or recall) as formulated in Eq. (6) reflects the model's ability to correctly identify true positives which makes it vital for minimizing false negatives—instances where porcine gelatin is present but incorrectly classified as absent. High sensitivity is crucial to prevent the unintended consumption of non-halal substances and to enhance consumer safety. The two metrics discussed are confusion matrix-based metrics, directly derived from the confusion matrix presented in TABLE 2 and are calculated as follows.

TABLE 2
Confusion matrix

	Predicted as Positive	Predicted as Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (6)$$

AUC (Area Under the ROC Curve) quantifies the model's ability to differentiate between classes, providing insight into overall performance across thresholds. A higher AUC indicates better discrimination capability for identifying Halal versus non-Halal gelatin sources, which is essential for ensuring compliance with Halal standards.

III. SYSTEM MODEL AND METHODS

A. ANALYTE PREPARATION

The primary analytes of interest are porcine (pig-derived), bovine (cow-derived), and fish gelatin, each sourced as commercially available pure product. The gelatin samples used in this study were prepared in solution form, with precise concentrations measured as a percentage by weight.

For the analysis, a 1% gelatin solution was prepared based on the assumption that higher concentrations would be more easily detectable. To create a 1% gelatin solution, 1 gram of gelatin was dissolved in 99 grams of deionized water. This mixture was then heated at 60°C and stirred at 200 revolutions per minute (rpm) for 7 minutes using a hotplate and magnetic stirrer to ensure complete dissolution and homogeneity of the solution. The objective of this study is to demonstrate the ability of a specifically configured gas sensor array to detect the presence of these gelatin analytes. The sensor array is designed to capture the distinct signals emitted by each gelatin type, based on the unique chemical properties of the porcine, bovine, and fish gelatin compounds.

B. DATA PREPARATION AND COLLECTION

The gas sensor configuration used in this research consists of seven sensor modules, each with selective sensitivity to ethanol, methane, propane, butane, ammonia, hydrogen sulfide, sulfur, and other organic solvent vapors. As shown in FIGURE 2, these seven modules are integrated within a sensor housing connected to an 8-bit microcontroller. To enhance the resolution of the analog sensor readings, a 16-bit ADC (Analog-to-Digital Converter) is employed.

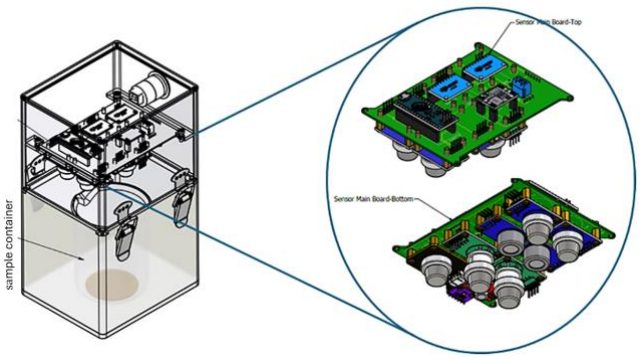

FIGURE 2. The configuration of the 7 gas sensor modules is integrated as a gelatin detection system.

The gas sensor modules operate by detecting changes in atomic, molecular, and ionic structures on the sensor surfaces, which are then converted into electrical signals. The e-nose developed in this study comprises seven metal-oxide semiconductor (MOS) gas sensors, as listed in TABLE 3. Data from each gas sensor module were collected to measure porcine, bovine, and fish gelatin analytes at two time points: immediately after preparation (0 hours) and two hours post-preparation

The e-nose system consists of two chambers: a gas sampling chamber, where the tested samples are placed, and an electronic box chamber, which houses the sensors responsible for detecting various VOCs. Seven sensors (S1–S7) are positioned within the electronic box chamber to interact with VOC molecules emitted from the gelatin samples at designed concentration levels. Data collection for each analyte was carried out over a 15-minute period, with the sensor operating in cycles of 60 seconds for data collection and 30 seconds for relaxation (purging). Over the 15-minute measurement window, the sensors produced approximately 723 rows of data across the seven gas sensor modules. The resulting sensor data are dynamic in nature, consisting of both data collection and purging periods, and cannot be directly analyzed using standard statistical methods due to their sinusoidal behavior. To address this, numerical methods were applied to compute the area under the sinusoidal curves generated by the sensor data. Following this preprocessing step, the data were further analyzed using advanced classification algorithms, such as DL models, to uncover the classification patterns of the analytes.

TABLE 3
Specification of chemoresistive sensors used in the e-nose system

Gas sensor	Sensor Type	Volatile compound target	Measurenment Range
S1[42]	Tin Dioxide (SnO2) /MOS	Alcohol, Benzene, Methane, Hexane, LPG and Carbon monoxide	1MΩ- 8 MΩ (0.4mg/L alcohol)
S2[43]	Tin Dioxide (SnO2) /MOS	LPG, Methane, Hydrogen CO, Ethanol	10KΩ- 60KΩ (1000ppm CH4)
S3[44]	Tin Dioxide (SnO2) /MOS	Butane, methane, propane, Carbon Monoxide and Alcohol	10KΩ- 60KΩ (1000ppm LPG)
S4[45]	Tin Dioxide (SnO2) /MOS	Methane, carbon monoxide, isobutane, n-hexane, benzene, ethanol, acetone	1 to 10 $k\Omega$ in ethanol at 300 ppm/air
S5[46]	Tin Dioxide (SnO2) /MOS	Ammonia, ethanol, hydrogen, and isobutane	900KΩ-4900KΩ (in air)
S6[47]	Tin Dioxide (SnO2) /MOS	Hydrogen Sulfide (H2S)	30KΩ-200KΩ (10ppm H2S)
S7[48]	Tin Dioxide (SnO2) /MOS	Ammonia (NH3), Nitrogen (NO2), alcohol, Benzene, smoke, CO2	2KΩ to 20KΩ in 100ppm CO

IV. RESULT AND DISCUSSION

A. PERFORMANCES OF EACH SINGLE MODULE ON TWO TIME POINT

In this section we evaluate the performances of each e-nose sensor module—S1, S2, S3, S4, S5, S6, and S7—in detecting the presence of porcine gelatin before they're integrated. The sensors' performances were compared across two time points: immediately after sample collection (0-hour) and 2 hours later. The data underwent pre-processing steps such as normalization and imputation of missing values using the means of the two nearest data points to ensure the robustness of the analysis as seen in FIGURE 3.

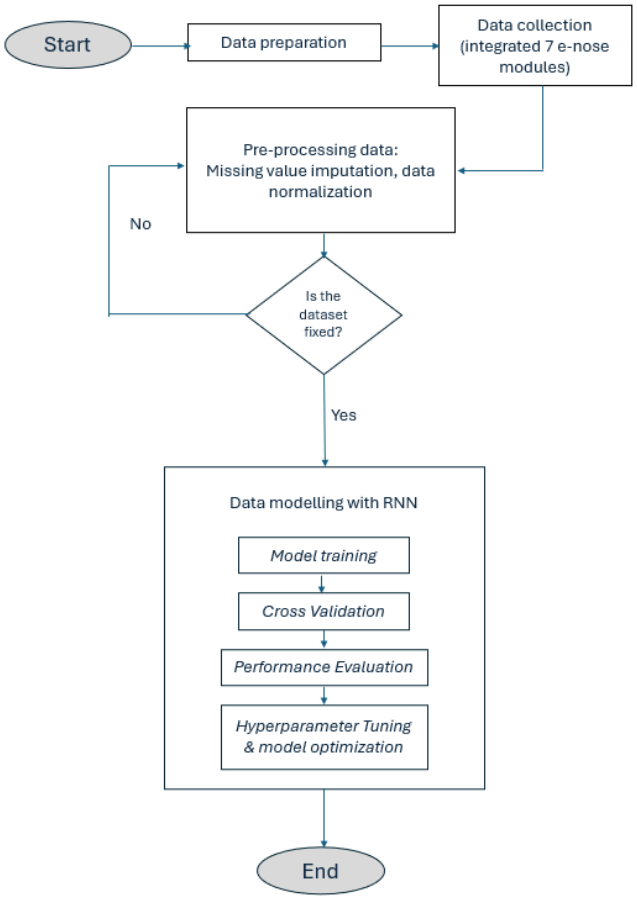

FIGURE 3. Flowchart of Data analysis

The metrics used to compare the performance were accuracy, sensitivity, and AUC for classification. Among the seven modules, S3 exhibited the highest accuracy of 87.6% at the 0-hour point as shown in FIGURE 4. This demonstrates that S3 is the most effective module in achieving correct predictions immediately after the samples are prepared.

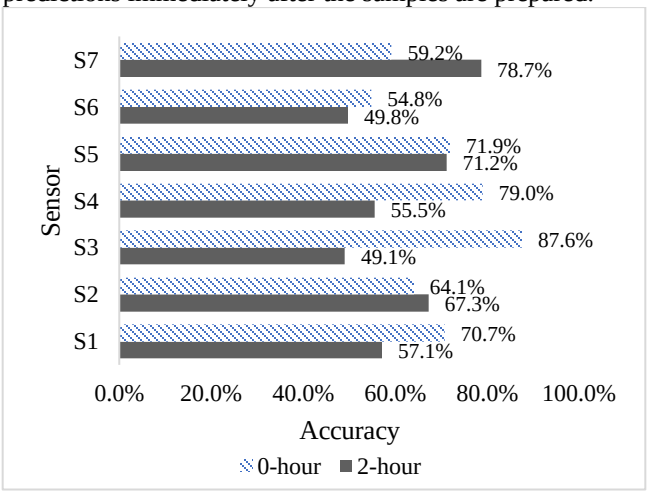

FIGURE 4. Accuracy comparison of seven sensor modules (S1, S2, S3, S4, S5, S6, S7) at two different time points (0-hour and 2-hour) post-sample collection

Sensitivity is especially crucial in the context of halal detection, where the primary concern is avoiding false negatives. In this scenario, a false negative occurs when a sample that contains pig derivatives (haram) is incorrectly classified as negative (halal). This kind of error is particularly problematic because it could lead to the unintended consumption of haram substances, which violates religious dietary restrictions. Given the sensitive nature of halal authentication, it is far more detrimental to incorrectly classify a contaminated sample as safe than the reverse. Hence, high sensitivity—like the 0.8790 achieved by S3 as shown in FIGURE 5—ensures that the module can reliably detect even small traces of pig derivatives, reducing the risk of false negatives and enhancing the trustworthiness of the detection system. By correctly identifying positive cases, the S3 minimizes the risk of certifying non-halal food products as permissible, which is essential for maintaining the integrity of halal food practices.

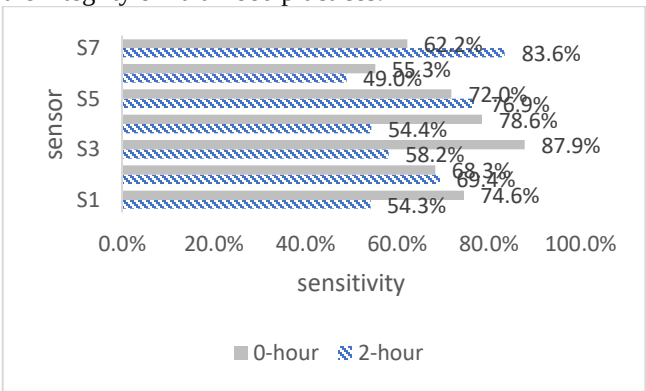

FIGURE 5. Sensitivity comparison of seven sensor modules (S1, S2, S3, S4, S5, S6, S7) at two different time points (0-hour and 2-hour) post-sample collection

The highest AUC is achieved by S3 module of 93.7% at 0-hour point as shown in FIGURE. 6. This suggests that the S3 module performs optimally at the initial time point, which has potential in offering a strong predictive capacity for the outcome being measured at the onset. The high AUC indicates excellent discrimination ability between the positive and negative classes.

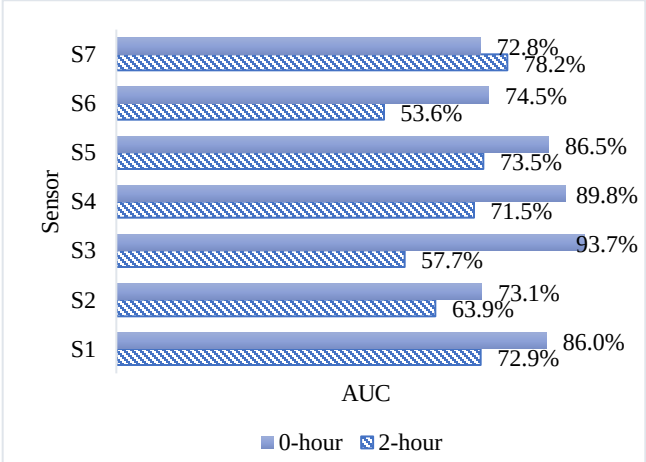

Figure 6. AUC (area under ROC curve) comparison of seven sensor modules (S1, S2, S3, S4, S5, S6, S7) at two different time points (0-hour and 2-hour) post-sample collection

The time of data collection plays a crucial role in the performance of the sensors. The analysis reveals that the performance of most sensors tends to decline after 2 hours of

post preparation. For example, the S3 module shows a marked reduction in accuracy (-38.5%), sensitivity (-29.7%), and AUC (-36%) when comparing the 2-hour point to the 0-hour point. This decline suggests that the sensor's ability to detect pig derivatives becomes less reliable as the samples age. A similar pattern was observed across most other sensor modules.

The 0-hour point data collection consistently produced better results across almost all sensors. For instance, S1, which showed slight improvements in accuracy (+2.2%) at 2 hours, experienced significant drops in sensitivity (-2.0%) and AUC (-28.9%), indicating that while it may still correctly classify a similar number of total samples, its ability to correctly identify true positive cases diminishes over time. In contrast, the S4 sensor also exhibited substantial performance drops after 2 hours, particularly in sensitivity (-24.2%), which further reinforces the recommendation to collect data as close to the sample collection time as possible.

Among the seven sensor modules, S3 exhibited the highest overall performance in terms of all three metrics. It achieved an accuracy of 87.5%, a sensitivity of 87.9%, and an AUC of 93.7% at the 0-hour point. These results suggest that solely, S3 is the most reliable sensor for detecting pig-derived gelatin when the data is collected shortly after the sample is taken. The high AUC indicates excellent model performance in distinguishing between the different classes, while the balanced accuracy and sensitivity imply that S3 is capable of both correctly identifying positive samples and minimizing false negatives.

While S3 emerges as the top performer, other sensors exhibit unique trends. For instance, S1 showed only a minor improvement in accuracy after 2 hours, but this improvement was overshadowed by sharp declines in sensitivity and AUC. This result suggests that the accuracy metric alone may not provide a comprehensive view of sensor performance, and sensitivity and AUC should be considered in conjunction. Sensors like S5 and S7 also demonstrated similar declines across all metrics after the 2-hour point. It reinforces the finding that time delays negatively impact the sensors' ability to distinguish between classes effectively.

B. SENSITIVITY OF EACH SINGLE MODULE FOR EACH GELATIN TYPE

For a more comprehensive analysis, TABLE 4 presents a detailed breakdown of the sensitivity of each e-nose module for detecting different gelatin classes—porcine (pig-derived), bovine (cow-derived), and fish. This comparative overview highlights the effectiveness of individual modules in accurately identifying specific gelatin sources. Based on the sensitivity data from each e-nose module (S1–S7) across two time points (0 and 2 hours), clear patterns emerge regarding the performance of each module in detecting pig-derived, cow-derived, and fish gelatin.

As shown in TABLE 4, sensors S1 and S3 demonstrated the highest sensitivity for pig-derived gelatin at the 0-hour point, with 95.7% and 90.6%, respectively, indicating their reliability for immediate detection. By the 2-hour point, S7's sensitivity increased to 0.882, showing its effectiveness in detecting porcine gelatin 2-hour post-preparation. In contrast, S6 75.2%) and S7 (72.7%) demonstrate the lowest sensitivity which indicates weaker performance in detecting pig-derived gelatin. For cow-derived gelatin, S3 (89.6%) performs exceptionally well, while S6 (42%) shows significantly lower performance. Fish gelatin detection at the 0-hour point is led by S4 (87.2%) and S3 (83.5%), with S6 demonstrating poor sensitivity (48.7%).

TABLE 4
Sensitivity performance of the modules across two time point on each class

	0-hour (%)			2-hour (%)		
Modul	Pig	cow	fish	pig	cow	fish
S1	95.7	53.8	74.3	51.5	69.2	42.1
S2	83.1	60.5	61.5	65.8	85.9	56.4
S3	90.6	89.6	83.5	47.2	48.9	78.6
S4	75.0	73.7	87.2	45.0	68.2	50.0
S5	75.4	57.4	83.0	78.4	95.5	56.6
S6	75.2	42.0	48.7	32.1	56.9	58.1
S7	72.7	52.8	61.1	88.2	100.0	68.1

At the 2-hour point, the performance of the modules shifts. S7 becomes the most sensitive for pig-derived gelatin detection, with a sensitivity of 88.2%, while S6 drops significantly to 32.1%, showing a marked decrease in detection capability over time. For cow-derived gelatin, S7 reaches perfect sensitivity (100%), with S5 (95.5%) also performing well. In contrast, S3 (48.9%) and S4 (68.2%) show weaker performance at the 2-hour point. While for fish gelatin detection, S3 (78.6%) and S7 (68.1%) remain the top performers, and S1 (42.1%) and S4 (50%) show significantly reduced sensitivity after 2 hours.

In summary, S3 and S7 emerge as the top performers across both time points. S3 excels at the 0-hour point, particularly for pig and cow-derived gelatin, but its performance declines after 2 hours. In contrast, S7 maintains strong and consistent sensitivity across both time points, making it the most reliable module for long-term detection, especially for cow-derived gelatin, where it achieves perfect sensitivity.

A key observation is the general decline in sensitivity over time for most modules, particularly in pig-derived gelatin detection. For instance, S1 drops from 95.7% at the 0-hour point to 51.5% at the 2-hour point. This highlights the importance of selecting the appropriate module based on the timing of sample collection. S7 proves to be the most robust module, demonstrating reliable sensitivity across all classes and time points, making it the most promising candidate for accurate detection of pig-derived gelatin, pig-derived gelatin, and fish gelatin.

C. PERFORMANCE OF INTEGRATED MODULES ON SINGLE DATA BASED ON TWO TIME POINT

This section aims to evaluate the performance of the integrated system comprising seven e-nose modules across three key metrics. The goal is to determine whether the integrated approach delivers superior results compared to the

performance of each individual module when used independently.

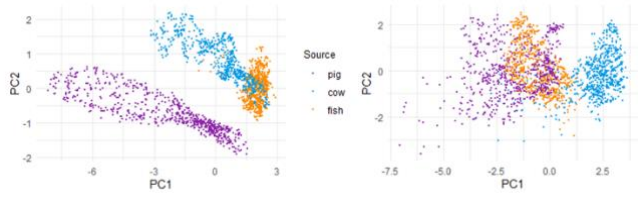

Figure 7. PCA plot for the data at (a) 0-hour and (b) 2-hour point

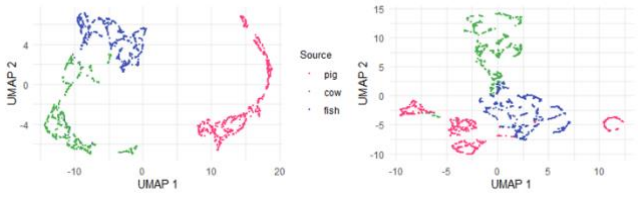

Figure 8. UMAP plot for the data at 0-hour (a) and 2-hour (b) point

Based on the PCA and UMAP plots in FIGURE 7 and FIGURE 8, the time points do influence the performance of the methods, but the differences are more nuanced. At the 0-hour time point, the classes appear to be well-separated, indicating that the samples can be more easily differentiated. This suggests that the signal data is more distinct shortly after collection, enabling more accurate classification of pig, cow, and fish gelatin.

At the 2-hour time point, however, the separation between classes becomes less distinct, with some overlap observed between the classes. This could indicate that the signal data starts to lose some of its distinguishing features over time, making classification slightly more challenging. However, it's important to note that the visual representation alone from PCA and UMAP plots cannot fully justify the model's performance. While the plots provide insight into how well the samples are separated, the actual performance metrics (accuracy, sensitivity, and AUC) should be carefully analyzed to validate the performance of this method in distinguishing sample from certain source. TABLE 5 provides a detailed overview of the performance of the integrated 7-module system at different time points. The table highlights key metrics, including accuracy, sensitivity, and AUC, allowing for a comparative analysis of the system's effectiveness in classifying gelatin types (pig, cow, fish) at the 0-hour and 2-hour point.

TABLE 5
Performances of integrated modules

	Accuracy	Sensitivity	AUC	Sensitivity for each class		
0hour	0.963	0.966	0.982	1.000	0.978	0.919
2hour	0.991	0.991	0.991	0.986	0.993	0.993

At the 0-hour point, the integrated system achieved strong overall performance, with an accuracy of 0.963, sensitivity of 0.966, and AUC of 0.982. Notably, the sensitivity for each class was high, with pig-derived gelatin detection at 1.000, cow-derived gelatin at 0.978, and fish gelatin at 0.919. These results demonstrate the system's ability to effectively distinguish between classes, particularly at the early time point, which corresponds with the better separation of classes seen in the PCA and UMAP plots.

At 2 hours, the performance of the integrated modules improved further, with an accuracy of 0.991, sensitivity of 0.991, and AUC also reaching 0.991. The sensitivity for each class remained high, with pig-derived gelatin at 0.986, cow-derived gelatin at 0.993, and fish gelatin also at 0.993. This suggests that the integrated system can still effectively distinguish between gelatin types even after 2 hours in comparison with individual module performance typically declined over time.

Overall, the integrated e-nose system outperformed the individual modules at both time points, demonstrating more consistent and reliable detection across all gelatin types. This highlights the advantage of integration, as combining multiple sensors mitigates the weaknesses of individual modules and enhances overall accuracy, sensitivity, and AUC.

D. PERFORMANCES OF INTEGRATED MODULE ON MIXED DATA

The model was also applied to mixed gelatin samples (pig-cow, pig-fish, and fish-cow) on one time point to assess whether the system could accurately detect the presence of porcine gelatin when mixed with other animal-based gelatin sources.

TABLE 6
Performance analysis of model applied to mixed gelatin

	Min	Max	Median	Mean
Accuracy	0.970	0.993	0.981	0.982
Sensitivity	0.967	0.995	0.980	0.979
AUC	0.961	0.994	0.983	0.981

The results in TABLE 6 shows high accuracy, ranging from 0.970 to 0.993, with an average of 0.982. This high accuracy shows that the model is highly effective at identifying whether porcine gelatin is present in mixed samples. The tight range between the minimum and maximum accuracy suggests consistent performance across different mixtures. This consistency implies that the type of animal-based gelatin mixed with porcine gelatin doesn't affect the model's accuracy, which has potential for practical use.

Sensitivity results are similarly strong, ranging from 0.967 to 0.995, with an average of 0.979. High sensitivity means that the model is adept at detecting porcine gelatin when it's present, with minimal probability of missing it. The small difference between the minimal and maximum sensitivity values (0.028) further highlights the model's reliability in detecting the presence of porcine gelatin in a mixture.

The AUC, which measures the model's ability to distinguish between samples with and without porcine gelatin, ranged from 0.961 to 0.994, with an average of 0.981. This high AUC score means that the model can accurately detect porcine gelatin while keeping false positives low, which is important for maintaining specificity and avoiding incorrect identifications.

These results show that the system has potential for implementation in automated quality control systems, where rapid and accurate identification of porcine content in mixed-gelatin products could provide both cost-effective and ethical solutions for industry compliance and consumer trust. Therefore, it can be concluded that this study contributes to and expands the existing literature on food authentication. Previous methods, such as spectroscopy, chromatography, and DNA-based assays, have been effective but often require extensive sample preparation, specialized equipment, and trained personnel. [34] and [49] demonstrated the potential of e-nose systems for meat authentication; however, their methods were limited to single-sample detection. Similarly, [50] focused on liquid food matrices, emphasizing adulteration detection in oils, while [38] explored ultrasonic-e-nose fusion for olive oil authenticity. Unlike these studies, the integration of RNNs in this research provides enhanced classification capabilities, particularly for complex and mixed sample scenarios, filling a critical gap in the field.

A deeper analysis reveals that the system's performance benefits significantly from its modular gas sensor array and data processing via RNNs. The enhanced sensitivity to VOC profiles at different time points suggests that the system can reliably adapt to variations in sample aging. For example, the detection of pig gelatin, which is critical for halal authentication, consistently achieved high sensitivity and accuracy across all all time-dependent experimental conditions. This highlights the system's reliability in real-world applications, such as industrial halal compliance monitoring or rapid on-site food safety inspections.

However, several limitations in this study must be acknowledged. First, this study focuses exclusively on gelatin authentication, leaving its applicability to other food matrices unexplored. Computational demands of the RNN-based signal processing also pose challenges for scalability, especially in resource-constrained environments. Future research should explore sensor optimization and lightweight ML and DL models to overcome these challenges.

The implications of this study are multifaceted. From a halal compliance perspective, the system offers a transformative solution for ensuring food authenticity, addressing growing consumer demand for transparent labeling. Its ability to process both single and mixed samples efficiently positions it as a valuable tool for industries seeking cost-effective and rapid authentication methods. Furthermore, the system's integration of RNN showcases the potential of DL in advancing sensor-based technologies, which pave the way for broader applications in food quality control, pharmaceutical product verification, and even environmental monitoring.

This study sets a strong foundation for future work in food authentication. By addressing its limitations, such as expanding its application to other food matrices and optimizing the hardware for industrial scalability, the system can achieve even broader utility. Additionally, exploring hybrid methods that combine e-nose technology with spectroscopy or DNA-based techniques could further enhance its accuracy and applicability in more complex detection scenarios.

V. CONCLUSIONS

The aim of this study was to evaluate the efficacy of an integrated electronic nose (e-nose) system for the detection and classification of gelatin sources, addressing the critical requirement for Halal authentication in food products. Performance analysis indicated notable variations in accuracy, sensitivity, and AUC across different time points. At the initial 0-hour time point, the system achieved an accuracy of 96.3%, sensitivity of 96.6%, and an AUC of 98.2%, with further improvements observed at the 2-hour mark, where all metrics reached 99.1%. Individual sensor modules displayed varying performance trends, with some demonstrating high initial effectiveness followed by a decline over time, while others exhibited incremental improvements.

The integration of these modules yielded significant enhancements in overall performance, surpassing the metrics achieved by standalone modules. This integrated approach effectively addressed the limitations of standalone modules and ensured consistent detection accuracy for all gelatin types across both time points. Additionally, the integrated system demonstrated robust performance when applied to mixed gelatin samples, achieving sensitivity and AUC values consistently exceeding 97%, thereby underscoring its versatility and reliability in handling complex datasets.

These findings underscore the potential of the integrated e-nose system as a practical and efficient tool for Halal authentication in food products, providing a reliable solution to meet the increasing demands of diverse consumers and the evolving food industry. Optimization of sensor selection and the timing of data collection were identified as critical factors for enhancing system performance and reliability.

Future research should focus on refining the integration process by improving algorithmic efficiency and exploring sensor synergy to further enhance detection accuracy. Furthermore, expanding the scope of e-nose technology to broader applications, including food safety, quality assurance, and industrial monitoring, could unlock its potential as a transformative tool for rapid and accurate detection across various domains.

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