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AI-driven Sensor Array Electronic Nose System for Authenticating and Recognizing Aromas in Spirit Samples

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The safety of food and beverages has emerged as an urgent concern, as adulterated food and drink can seriously affect human health when consumed. Within this context, the spirits industry stands out as a sector that requires particular attention, as spirits such as whisky, gin, and vodka possess distinct flavor and aroma profiles intrinsically linked to their alcohol composition. To prevent adulteration and ensure the authenticity of spirits, it is essential to identify the purity of specific aroma compounds. In this work, we employed an electronic nose system with an AI algorithm to extract the scent profiles of various whisky spirits, generating their unique aromatic signatures.The AI algorithm demonstrated exceptional performance in classifying different whisky types, achieving an accuracy of 93% to 94%, depending on the type of whisky. Among the models tested, the convolutional neural network-long short-term memory (CNN-LSTM) model consistently outperformed other architectures, including traditional recurrent neural network (RNN), CNN, and LSTM models. The CNN-LSTM model exhibited the highest accuracy and lowest loss, highlighting its superior capability in capturing the complex aroma patterns of whisky spirits. This study represents a significant step forward in ensuring the integrity of spirits; a method for the rapid identification of spirits purity is also provided.

1. Introduction

Food safety and quality control have been vital concerns throughout human history. In the context of spirits, food safety has become an urgent issue, as the consumption of adulterated products can severely impact human health. Counterfeit spirits have thus become a major problem, undermining consumer trust in local alcohol markets and causing fatalities and severe health complications.(1) Alcohol content can affect both the safety and sensory quality of the drink. The accurate determination of alcohol purity is crucial, especially in the restaurant industry, where precise alcohol-to-water ratios are essential for creating balanced mixed drinks and cocktails. Traditional methods for measuring alcohol content can be time-consuming and may not provide the precision needed for efficient use in beverage preparation. To address this,

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we employed an electronic nose (e-nose) system with an AI algorithm to analyze the scent profiles of various types of whisky spirits, thereby providing a reliable method for verifying spirits purity.

The e-nose system, equipped with sensors responsive to volatile organic compounds (VOCs) in the spirit's aroma, generates unique aromatic signatures that correlate with the alcohol content and other sensory characteristics of the spirits. By applying a deep learning model, specifically the convolutional neural network-long short-term memory (CNN-LSTM) algorithm, we achieved high accuracy—ranging from 93% to 94%—in distinguishing the purity of different whisky samples. The CNN-LSTM model combines the strengths of CNNs and LSTM networks, making it an effective tool for recognizing and classifying different alcohol concentrations, even in complex mixtures. This allows for precise monitoring of alcohol content, which is particularly useful in ensuring the consistency of mixed drinks, where the spirits ratio plays a critical role in the flavor profile.

Spirits, or distilled alcoholic beverages, represent a diverse category of consumer products with significant cultural importance, valued globally for their unique flavors and complex production processes. In this research, spirits are defined as alcoholic beverages produced by distilling fermented substrates, including grains, fruits, or other sugar sources. This process, unlike the fermentation used in beer and wine production, results in beverages with significantly higher alcohol content, typically around 30–50% alcohol by volume (ABV).(2) The defining characteristic of spirits lies in the distillation process, which involves the selective boiling and concentration of ethanol and flavor compounds from the fermented substrate, resulting in a purified and concentrated liquid.(3) The variety of spirits is extensive, influenced by factors such as the raw materials used, production method, and geographical and cultural backgrounds. In this study, we focus on whisky, a spirit typically made from various malted grains and characterized by aging in wooden casks or barrels.(4) The distinct brewing methods of different distilleries result in a wide range of rich flavors and aromas in various types of whisky.

Whisky consumption involves various drinking methods. According to a previous study,(5) the aroma dispersion in the mouth varies with different whisky-to-water ratios. At an optimal ratio, the drinking experience is enhanced. The authors of this study also noted that at a 6:4 whisky-to-water ratio, evaluators could no longer accurately distinguish the whisky. The use of e-nose technology can precisely differentiate the type of whisky when human olfactory senses fail, recording the odor characteristics at different concentrations. This approach offers a reference for digitizing aromas in whisky consumption and cocktail mixing.

In view of this, recognizing the authenticity of spirits has become increasingly important, attracting academic interest from various analytical perspectives. In numerous studies, laboratory-based analytical instruments have been utilized. For example, Zhang *et al.*(6) developed an advanced analytical technique combining headspace solid-phase microextraction (HS-SPME) with gas chromatography-mass spectrometry (GC-MS) to identify aroma compounds in Baijiu (a Chinese liquor), enabling classification through the chemical characteristics of samples. Similarly, Mu *et al.*(7) used HS-SPME and comprehensive 2D gas chromatography–time-of-flight mass spectrometry (GC×GC-TOFMS) to measure trace aroma compounds in Baijiu. In addition, there is a substantial body of research utilizing GC-MS for food-related studies, including its application in the analysis of braised chicken, Pu-erh tea, and perilla leaves.[8–10] However, this method is associated with high costs and lengthy analysis times and necessitates skilled technicians for operation.[11] We further explored portable and noninvasive methods, the efficacy of portable Raman spectrometers in measuring alcohol content, and the identification of potentially hazardous alcohols in whisky samples, a crucial step in ensuring product safety and authenticity. Data analysis techniques such as principal component analysis (PCA) and partial least squares (PLS) regression applied to Raman spectral data facilitated the development of models for predicting ethanol content and detecting toxic alcohols such as methanol. Likewise, Liu *et al.*[12] introduced a novel machine-learning-enhanced batch Raman spectroscopy method for the simultaneous quantitative and discriminative analysis of various quality indicators in whisky samples.

On the other hand, numerous groups have utilized gas sensors to create e-noses for problem-solving through odor detection. For instance, in the medical field, Binson *et al.*[13] proposed using e-noses for lung cancer diagnosis. In the food industry, Aghdamifar *et al.*[14] employed an e-nose device combined with GC-MS data and statistical analysis techniques to successfully estimate the caffeine content in coffee bean samples. Moreover, Machungo *et al.*[15] explored the potential of e-noses to detect aflatoxin contamination in maize, with classification accuracy ranging from 58 to 88%. The results of these studies demonstrate that using e-noses for noninvasive detection is an effective and cost-efficient method.

The ability of the pattern recognition algorithm to analyze e-nose signals is the key to the success of the e-nose system. In terms of the selection of algorithms for e-nose systems, several machine learning and deep learning approaches for aroma identification in coffee, beverages, and food have been explored in the literature.[16] In our previous study, we conducted comprehensive benchmark analyses of AI models to predict the odor profiles of different spirits.[17] Our experiment results demonstrated that both CNN and CNN-LSTM models are well-suited for spirit discrimination in e-nose systems. Notably, the CNN-LSTM model outperformed the CNN model in terms of both accuracy and loss. Consequently, in this study, we employed the CNN-LSTM model as the algorithm for our e-nose system. The CNN-LSTM architecture combines the strengths of both CNNs and LSTM networks, making it an effective choice for time-series forecasting tasks. Livieris *et al.*[18] demonstrated its performance in gold price forecasting. Guo *et al.*[19] proposed its use for predicting odor descriptor ratings, whereas Elmaz *et al.*[20] applied it to indoor temperature prediction. In this work, we used the CNN-LSTM model as the main algorithm to verify the authenticity of spirits (i.e., whisky).

In this paper, we introduce e-nose technology as an innovative solution that mimics human olfaction. Comprising sensor arrays responsive to various VOCs, e-noses have potential applications in the food and beverage industries, including distinguishing different types of spirits and identifying alcohol-to-water ratios in alcoholic beverages. The proposed approach integrates e-nose technology with a dimensionality reduction method and deep learning technique to provide an automated system for rapidly verifying the aroma fingerprints of different authentic spirits. Our goal is to utilize an e-nose to detect odor compounds in the aromas of spirits, integrating AI techniques to rapidly identify the purity of the spirits based on their aromatic characteristics, thereby providing a reliable method for verifying the authenticity of spirit purity.

2. Materials and Methods

2.1 Collecting whisky samples

In this study, the whisky samples were selected referring to the regulations set by the European Parliament, which define spirits as beverages with a minimum alcohol content of 40%.(21) This standard ensures that the selected samples meet the legal classification of "spirits" within the EU. The diversity in production methods results in various whisky, each with distinct aromas and characteristics. The whisky-to-water ratios in this study were based on the everyday drinking habits of whisky consumers. Many whisky drinkers add a small amount of water to their whisky to enhance its flavor, but excessive dilution can make the drink overly mild and alter its taste profile. Therefore, we chose these specific ratios to ensure we captured a realistic range of whisky flavor intensities during testing. The details of the well-known whisky samples used in this study are listed in Table 1.

In this study, 45 records were collected for each whisky type, with 15 records for each of the three blend ratios: 100, 80, and 60%.

2.2 E-nose systems

In this study, we developed a customizable e-nose system that utilizes sensor array technology to identify the specific aroma compounds present in spirits. The metal-oxide semiconductor sensors employed in this system are low-cost and effective in detecting the VOCs from the vaporized scent of whisky samples. Table 2 presents the sensor used and the targeted specific gas. The sensor array is utilized to detect the VOCs that evaporate from spirits drinks. Additionally, throughout the experiment, we employed a temperature-humidity sensor module (i.e., DHT22) to measure the temperature and humidity.

To ensure the consistency of the experimental samples, we maintained a constant external resistance of 1 kΩ for the sensors throughout the experiment. We did not replace the sensors during the experimental period. Moreover, the temperature of the experimental environment

Table 1
Spirits characteristics and specifications.

Source	Blend ratio (%)	Key material	Country of origin	Original alcohol concentration (%)
Johnnie Walker	100	Malted cereals	Scotland, UK	40
	80			
	60			
Jack Daniel's	100	Wheat	Tennessee, USA	40
	80			
	60			
The Famous Grouse	100	Malted cereals	Scotland, UK	40
	80			
	60			

Table 2
Sensors used and targeted specific gas.

Sensor	Identified gas
TGS2600	Methane, carbon monoxide, butane, ethanol, hydrogen
TGS2602	Toluene, ammonia, ethanol, hydrogen,
TGS2603	Amine series, sulfurous odors
TGS2610	Ethanol, hydrogen, methane, butane, propane
TGS2611	Ethanol, hydrogen, methane, butane
TGS2620	Methane, carbon monoxide, butane, hydrogen, ethanol
TGS813	Methane, propane, butane,
TGS822	Ethanol, organic Solvent

was regulated at 27 °C ± 2 to uphold stable testing conditions. The internal temperature of the e-nose was also maintained within the range of 30 °C ± 3, and humidity was controlled at 30% ± 5 using an activated carbon filter to reduce the impact of environmental variables on the experimental outcomes.

2.3 Activated Carbon Filters

To mitigate interference from external environmental factors in the data collection of the e-nose, we employed an activated carbon filter to purify the air before it entered the sample container and e-nose. The porous structure of activated carbon provides a large surface area that allows it to effectively adsorb pollutants and impurities from gases and liquids and is widely used in water treatment and air purification. This approach ensured that only clean air was present in the experimental container, thereby enhancing the accuracy and reliability of the data.

2.4. Illustration of system framework

Figure 1 shows the system framework. The work began with the preparation of whisky samples. After an appropriate duration of an air-filtering process, we then took some samples of spirits and stored them in the container to collect their aroma. The aromatic gas was then delivered to the e-nose device and interacted with sensors in the e-nose system. Then, the sensor output data were collected and preprocessed to use the algorithm on as much useful data as possible. The extracted aroma dataset was used to train the selected machine learning models for the recognition task. The machine learning model, similar to how the human brain functions, learned the major features of the tested spirits aroma in order to perform the recognition of the spirits aromas. In this study, we utilized an e-nose system for spirits-aroma sensing. Before each test, the system underwent a cleaning process to guarantee the accuracy and stability of the sensors. After data collection was completed, we performed data analysis. The detailed description of each step is as follows.

First, for air filtering, external air was drawn into the system using a vacuum pump and passed through an activated carbon filter to ensure that the air entering the e-nose was purified. After that, we started to create a baseline internal environment within the system in preparation for subsequent sensing operations. The process of aroma data acquisition is illustrated in Fig. 2.

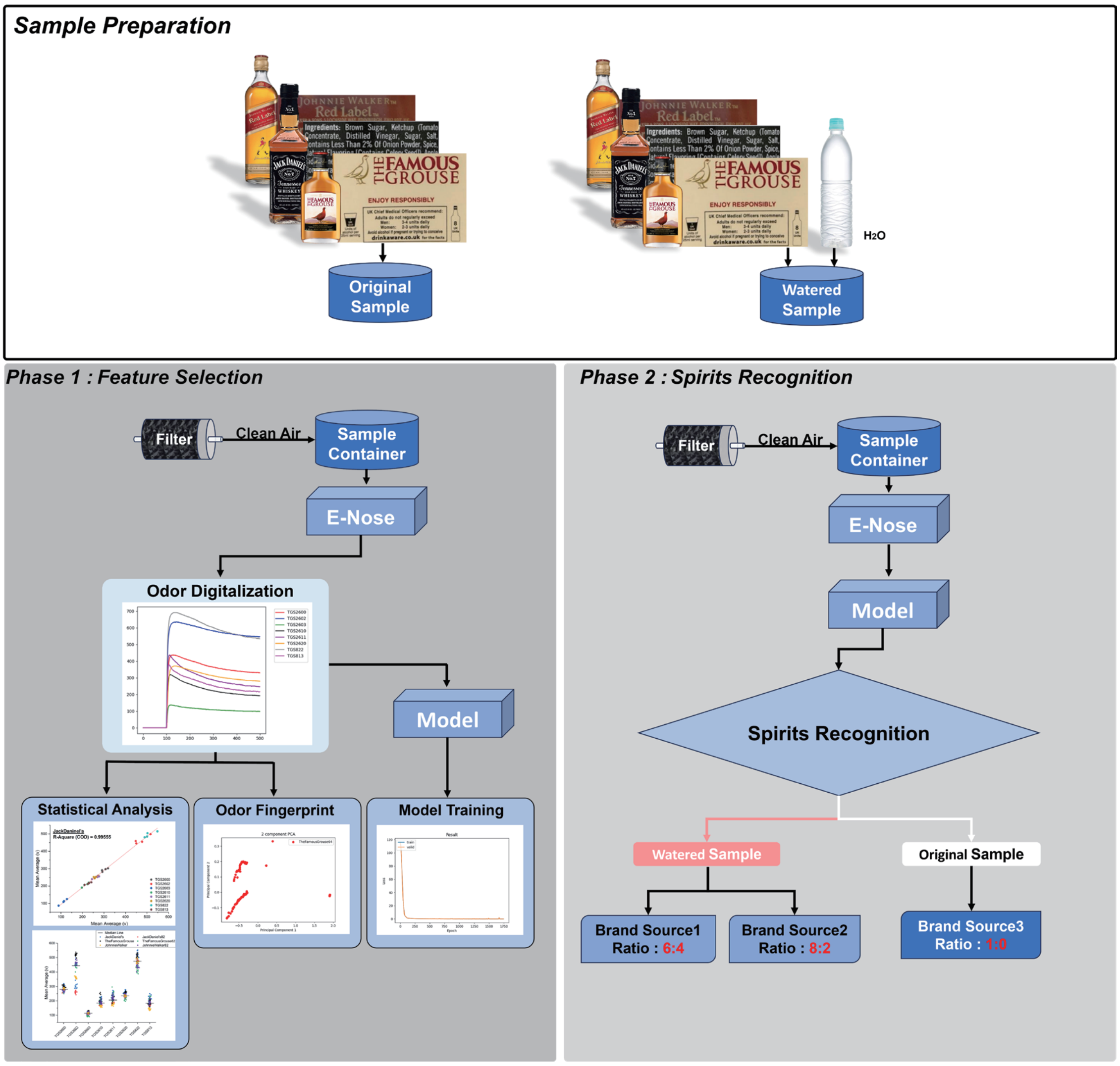


Fig. 1. (Color online) System framework.

2.5 Sample preparation

The process of preparing samples is critical for our study. We used a syringe to extract samples from whisky bottles and inject them into a 20 ml test container. Each test sample contained 2 ml of whisky. For the water-blended samples, pure water was extracted using a syringe and injected into the mixing container, followed by the addition of pure whisky. The mixed solution was prepared by combining whisky and pure water in specific proportions. These preparation steps ensure the consistency and accuracy of each test sample, as depicted in the process flowchart.

2.6 Baseline recovery

To maintain accuracy, after each test, we repeated the cleaning steps of the e-nose system. This involved rotating the gas three-way valve again to flush the system with filtered air,

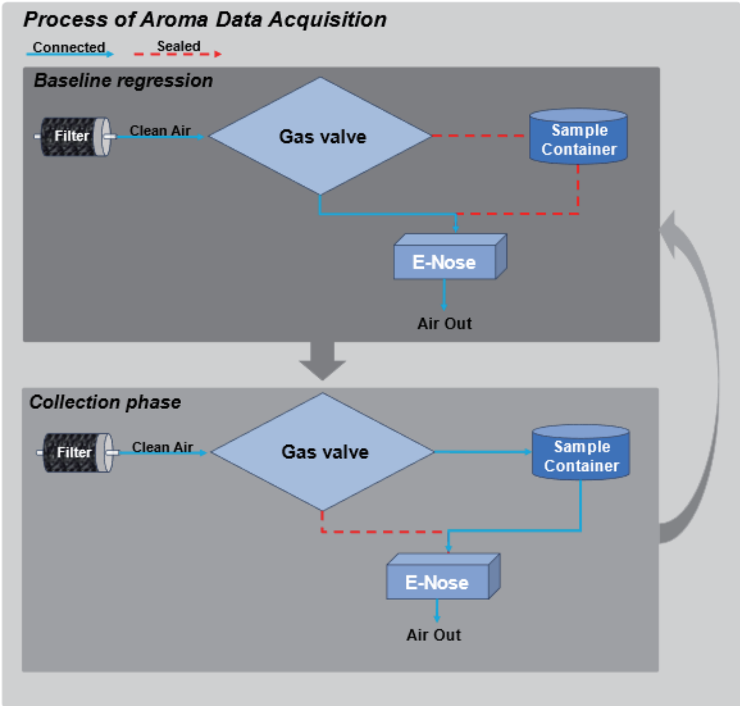


Fig. 2. (Color online) Process of aroma data acquisition.

allowing time for the sensors to return to a baseline state before proceeding with the next round of testing.

2.7 Sample collection

Once the samples were injected into the container, we connected the pipeline and activated the vacuum pump. Within the first 100 s, we ensured again that the sensor values were in a baseline state. At this stage, gases from the test samples had not entered the e-nose system. After 100 s, we rotated the gas three-way valve to introduce filtered air into the sample container, thereby introducing the odor from the sample container into the e-nose system for odor data collection.

3. Experiments and Results

In this study, an e-nose system was used to record the transient response of multiple sensor elements when exposed to the VOCs emitted from various whisky samples. As depicted in Fig. 3, the sensor array exhibited diverse response patterns across the various types of spirits over time. This data acquisition process enabled the comprehensive assessment of the odorant profiles, laying the groundwork for further analysis using advanced machine learning techniques. The distinctive response signatures detected indicate that this e-nose system can efficiently capture the aroma profiles of spirits, a critical step in identifying potential adulteration

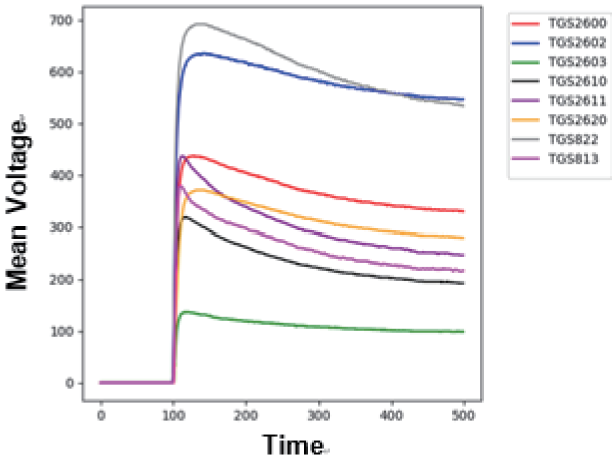
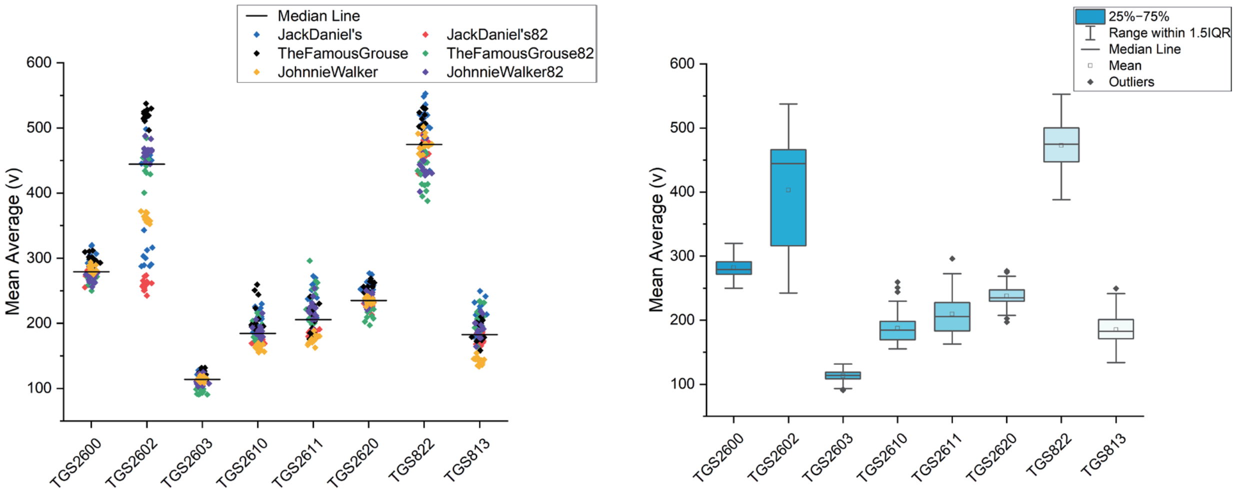


Fig. 3. (Color online) Examples of extracted data of spirits aroma profiles.

or counterfeiting. The various scent profiles of each spirits sample are depicted by the mean average value of the sensor responses in Fig. 4. When compared with other classes of specialty spirits, gin spirits have the highest ABV, which validates that they have the strongest fragrance over sensor arrays. However, each spirits sample has a specific range that corresponds to its aromatic characteristics. As a result, various aromatic patterns are generated, each of which reflects the unique characteristics of the sample.

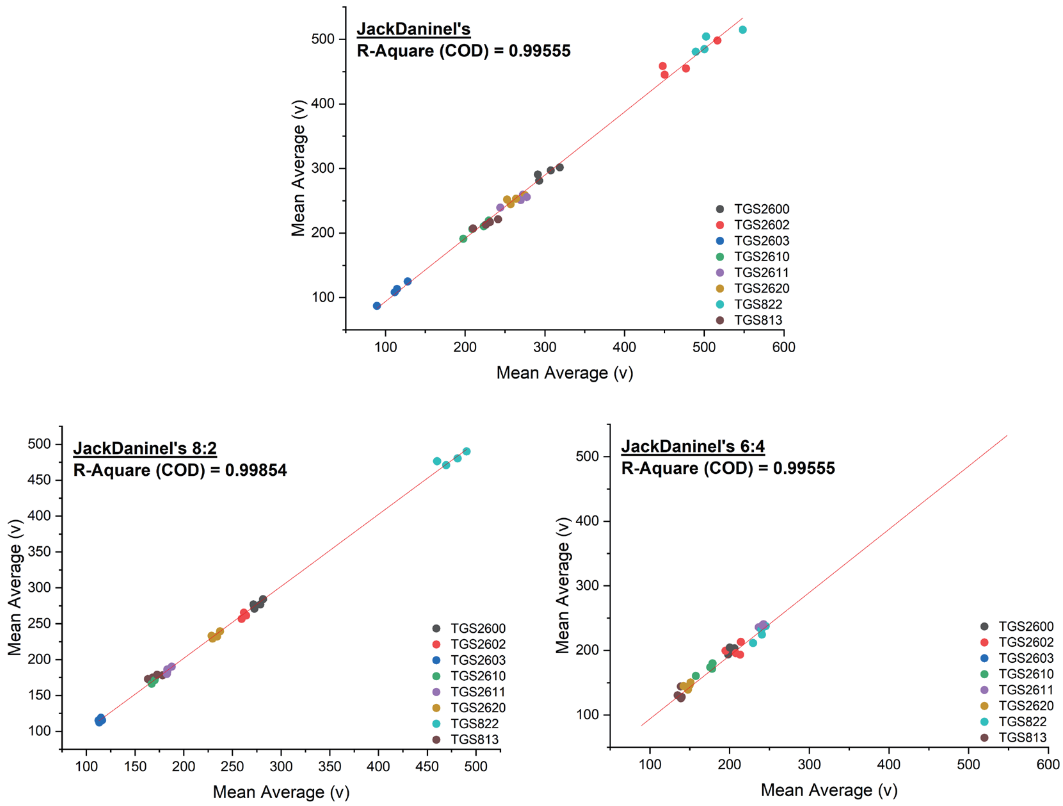
In Fig. 5, the average voltage responses of eight gas sensors to different whisky samples are compared. Each subplot represents a specific whisky sample measured under various mixing ratios, with the corresponding R^2 values (coefficient of determination) indicating the consistency of sensor responses across different ratios and sensors. The high R^2 values across subplots suggest a strong linear correlation in responses, reflecting high consistency and reliability of measurements for each whisky sample across sensors. Despite the overall high correlation in responses, slight variations in response patterns between different whisky samples are observable, indicating some degree of sensor-specific sensitivity. Notably, the TGS2602 sensor shows a few data points with larger deviations in certain samples, which may reflect the distinct sensitivity characteristics of this sensor when exposed to specific whisky compounds. These results demonstrate that the tested gas sensors possess both sensitivity and stability, effectively differentiating between whisky samples on the basis of their distinct response patterns. The high correlation of responses across sensors suggests minimal variability, thus supporting the potential for these sensors in future sample identification and odor analysis applications.

Figure 6 shows the response of our e-nose system to sudden changes in external odors. To demonstrate the differences, data collection with the e-nose system was conducted for 100 s. At the 10 s mark, a 20 ml container containing 1 ml of alcohol was introduced. The left side of the image shows the response without filtration, whereas the right side shows the response after passing through activated carbon filtration. There are significant differences in both peak values and affected duration between the two conditions. In this simulation, although the data after activated carbon filtration still exhibit variations, typical environmental odor fluctuations do not



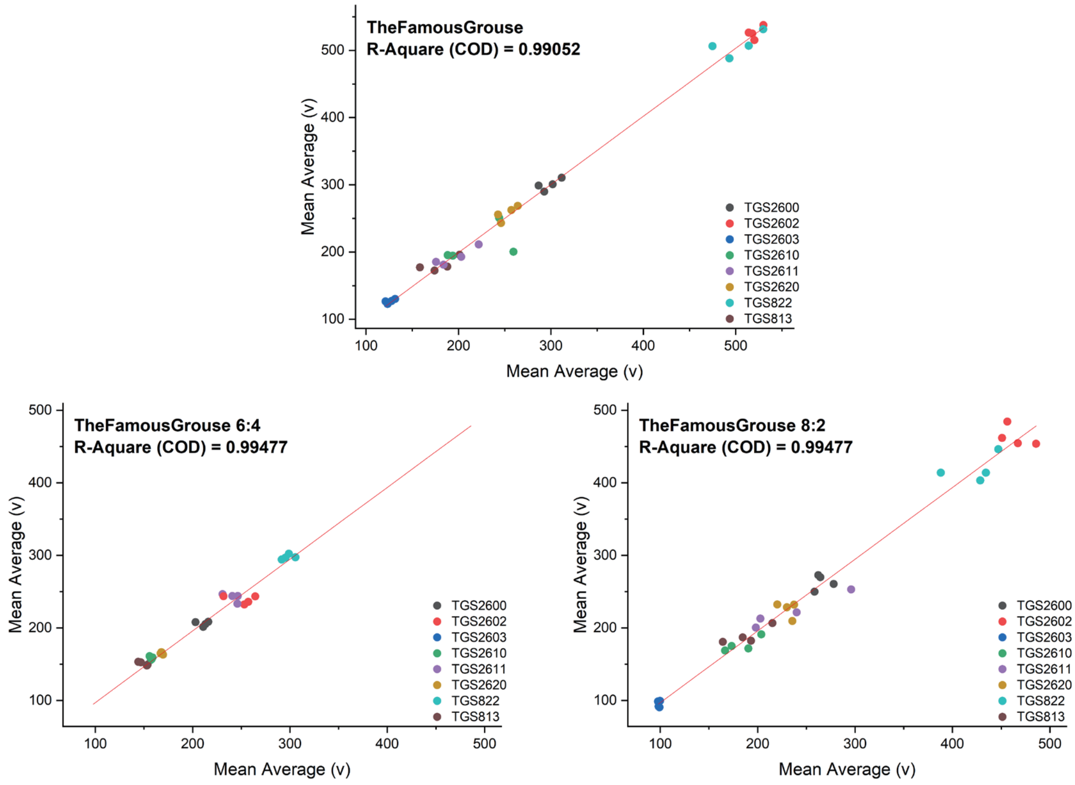
(a) (b)

Fig. 4. (Color online) Mean average values of spirits profile-based sensor array.



(a)

Fig. 5. (Color online) Linear regression fit of various spirits data samples. (a) Jack Daniel's, (b) The Famous Grouse, and (c) Johnnie Walker.



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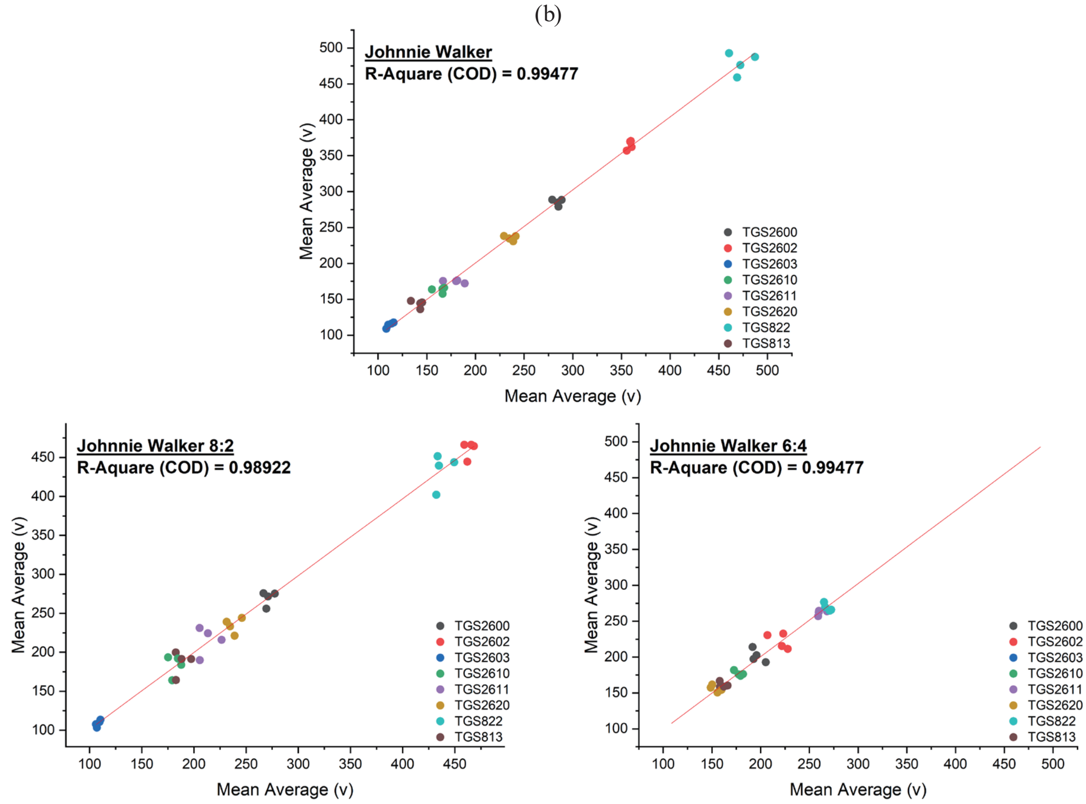


(c)

Fig. 5. (Color online) (Continued) Linear regression fit of various spirits data samples. (a) Jack Daniel's, (b) The Famous Grouse, and (c) Johnnie Walker.

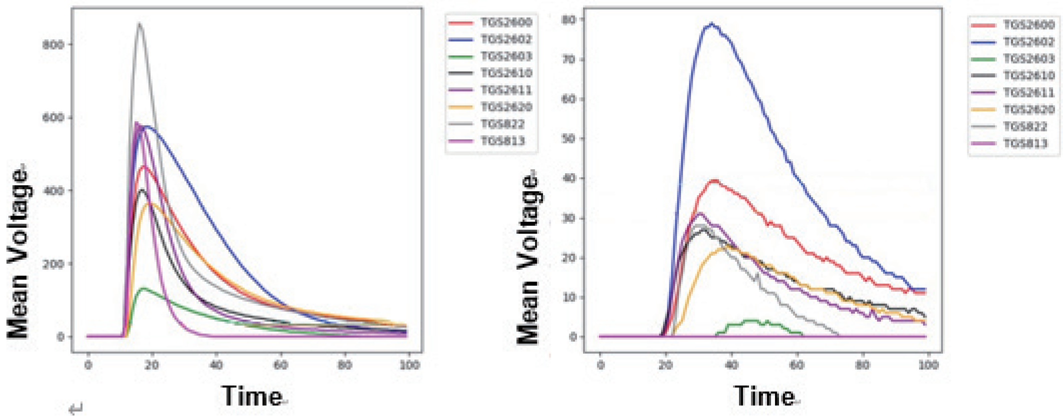


Fig. 6. (Color online) Linear regression fit of data samples of various spirits.

affect the data. For example, using alcohol for disinfection or consuming odorous foods in the same space may affect the data collection of the sensors.

3.1 Evaluation of CNN-LSTM model for multiclass whisky samples

For the preliminary experiments, data were collected from three different types of whisky, resulting in 45 data points. This dataset was used to evaluate the performance of various models. The initial experiments were aimed at determining which model would best capture the patterns in the data and provide reliable predictions. As shown in Table 3, the performance of four models—recurrent neural networks (RNNs), CNNs, LSTMs, and a hybrid CNN-LSTM model—was evaluated based on accuracy and loss. The CNN-LSTM model achieved the highest accuracy of 0.93 and the lowest loss of 0.58216, outperforming the other models. While both the LSTM and CNN models achieved an accuracy of 0.91, the CNN-LSTM model demonstrated superior performance with a lower loss than that of the CNN (loss = 0.65548) and LSTM (loss = 0.61002) models. Given these promising results, the CNN-LSTM model was selected for further analysis, as it demonstrated the best overall performance in terms of both accuracy and loss, making it the most suitable choice for the task at hand.

3.2 Evaluation of CNN-LSTM model for multiclass whisky samples

As discussed previously, in this study, we employed the CNN-LSTM model as the algorithm for our e-nose system. Figure 7 show the training and validation performances of the machine learning model utilized to evaluate multiclass whisky samples. Figure 8 shows the progression of the model accuracy with fluctuations during training. Evaluating the training model is pivotal in developing an e-nose system capable of accurately identifying and classifying different whisky samples on the basis of their unique aroma profiles. As indicated in Table 4, the CNN-LSTM model achieved a high average precision of 0.94 (i.e., 94%). Monitoring loss metrics during training and validation phases, along with precision, ensures the model's robustness and its ability to reliably authenticate the purity and authenticity of various spirits products.

Table 3
Evaluation results of model accuracy and loss.

Model types	Best accuracy	Best loss
RNN	0.89	0.62054
CNN	0.91	0.65548
LSTM	0.91	0.61002
CNN-LSTM	0.93	0.58216

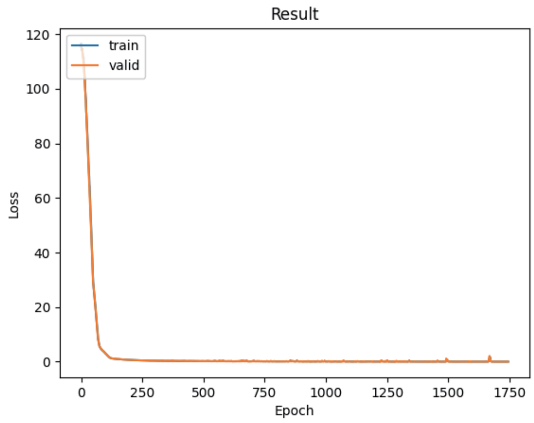


Fig. 7. (Color online) Training performance of whisky samples.

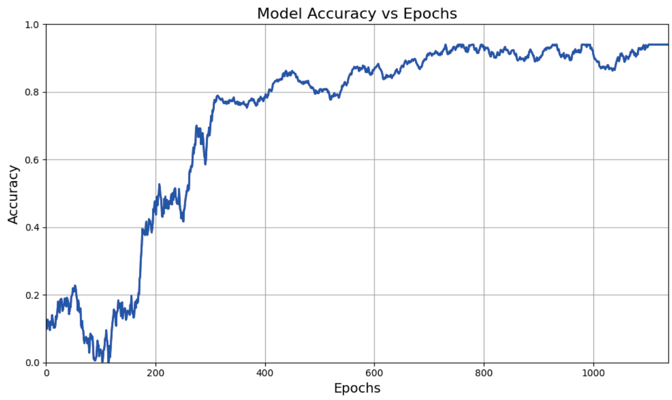


Fig. 8. (Color online) Accuracy progression and fluctuations during model training.

Table 4
Training evaluation results for various whisky samples.

Spirits type	Blend ratio	Precision	Recall	*F*1-score
	1:0	0.94	0.95	0.95
Johnnie Walker	8:2	0.95	0.95	0.95
	6:4	0.92	0.92	0.92
	1:0	0.94	0.94	0.94
Jack Daniel's	8:2	0.96	0.96	0.96
	6:4	0.95	0.95	0.95
	1:0	0.94	0.94	0.94
The Famous Grouse	8:2	0.95	0.95	0.95
	6:4	0.93	0.93	0.93

After collecting data from three whisky brands, we initially trained our model using 45 pure whisky samples (15 samples from each of the three whisky brands). The model achieved an overall accuracy of 0.93 on the validation set. We then gathered 135 mixed whisky–water samples, with 45 samples per whisky brand at two different water-to-whisky ratios (80% whisky: 20% water and 60% whisky: 40% water). The model was retrained on the mixed whisky–water data, achieving an overall accuracy of 0.94, as shown in Table 5.

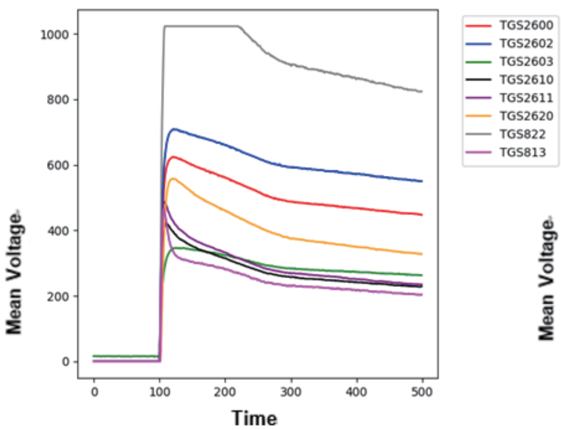
During the experimental process, we noted that the intake port of the whisky sample container significantly affected the collected data. When the sample was directly blown into the intake port, the alcohol evaporated too quickly, resulting in excessively high gas concentrations inside the e-nose and sensor readings exceeding the threshold, rendering the collected data unusable. Thus, we avoided directing the intake port directly toward the sample. As depicted in Fig. 9, the left side represents before adjustment, and the right side represents after adjustment.

Additionally, we analyzed the duration of data collection, conducting data collection for 1500 s and observing data variations over time. For Jack Daniel's as an example, in the samples with high water content in Fig. 10, the period from 0 to 100 s represents the filtered air phase, with the gas valve opening at 100 s. The 100–200 s period corresponds to the rising phase, followed by a plateau phase after 200 s. Subsequent overlapping data intervals occur between 300–400 s, 600–800 s, and 1000–1200 s.

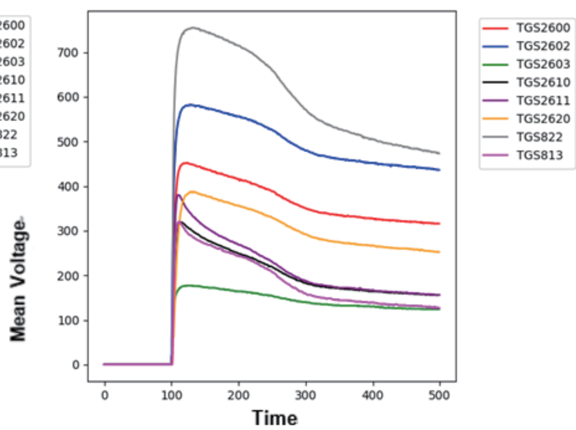
According to our observations and experimental results, the data did not yield better training outcomes for the model after 500 s. We conducted tests on data extraction time lengths ranging from 50 to 300 s, 50 to 200 s, and other durations, in addition to the full 500 s data length, to strike a balance between time and accuracy in model training. The model was trained with an

Table 5
Model training results.

Model data type	Best accuracy	Best loss	epoch
Pure Whisky	0.93	0.58216	1372
Pure Whisky and Water Mixture	0.94	0.03039	1137



(a)



(b)

Fig. 9. (Color online) Data plots (a) before and (b) after adjusting the experimental container.

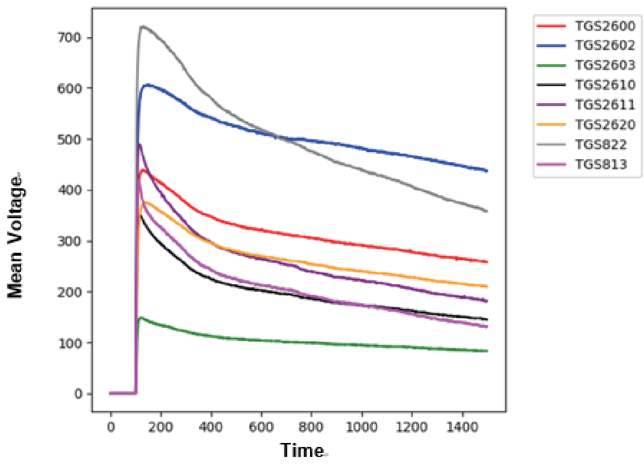


Fig. 10. (Color online) Variations in sensor response over time for Jack Daniel's.

epoch setting of 2000 s to prevent overfitting, and early stopping was implemented with a setting of 500 s. The training results of the model are presented in Table 6.

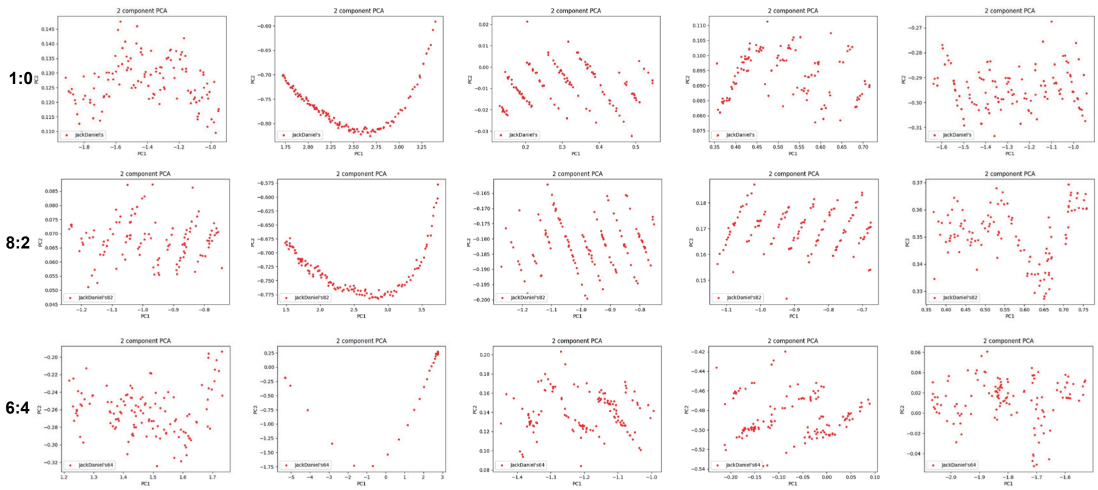
3.3 Generation of odor fingerprints of tested whiskies

Each whisky sample has distinct flavor and odor characteristics. In this study, we utilized the collected odor data to generate a unique “odor fingerprint” for each sample and visualized these characteristics. By reducing the dimensionality of the data using PCA, we retained most of the variation in the dataset while highlighting the key features of each sample.

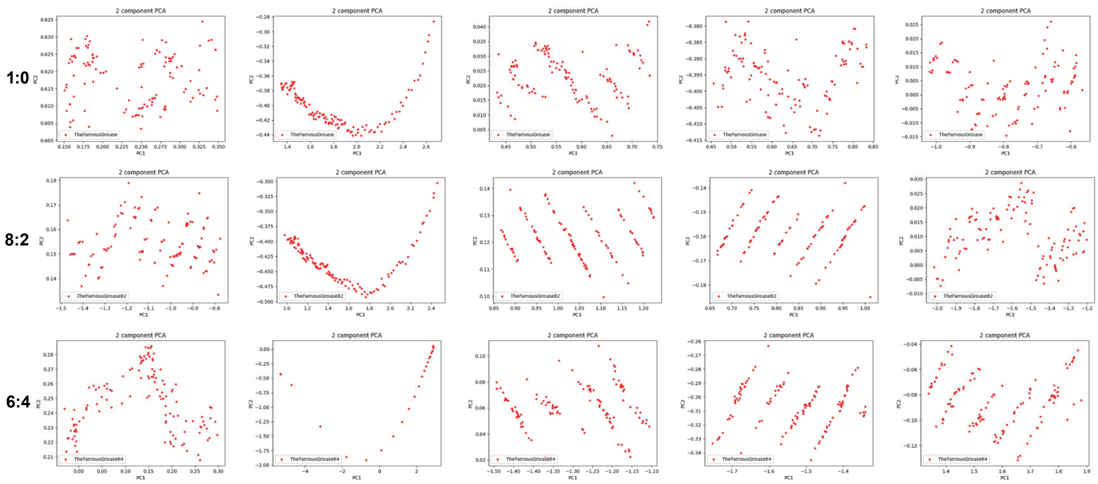
After reducing the dimensionality of the data using PCA, the main features of each sample were visualized while retaining most of the variation in the data. The first row of Fig. 11 shows the PCA results for samples labeled ‘Jack Daniel’s.’ The data points of these samples are concentrated within a relatively narrow range on the first and second principal components, indicating consistent odor characteristics among these samples. Similarly, the second row depicts the distribution of ‘The Famous Grouse’ samples, and the third row shows the distribution of ‘Johnnie Walker’ samples. Significant differences in odor characteristics among different whisky brands can be observed by comparing these distributions. This allows for identifying and differentiating unique odor fingerprints among different whisky samples. This analytical approach enhances the understanding of whisky odor characteristics and has practical applications in quality control and product authentication. However, certain regions in the visualizations may be hard to distinguish, particulary when the odor profiles of the samples are more similar. This challenge is akin to human fingerprints—while each fingerprint is unique, family members’ fingerprints often share similar patterns, making it difficult to distinguish them at a glance. Likewise, whisky samples with similar odor profiles may appear closer together in the PCA plot, reflecting their subtle but shared characteristics. In such cases, the visual overlap of data points may not fully capture the nuanced differences in scent, which are more easily detected through specialized analytical methods.

Table 6
Data extraction time lengths.

Extraction Time (s)	Best accuracy	Best loss	Epoch
500	0.94122	0.03039	1137
50–400	0.94122	0.34081	1659
50–300	0.94561	0.12129	2000
50–200	0.93122	0.15406	2000
100–400	0.93122	0.10575	2000
100–300	0.93122	0.10135	2000
100–200	0.93122	0.10075	2000

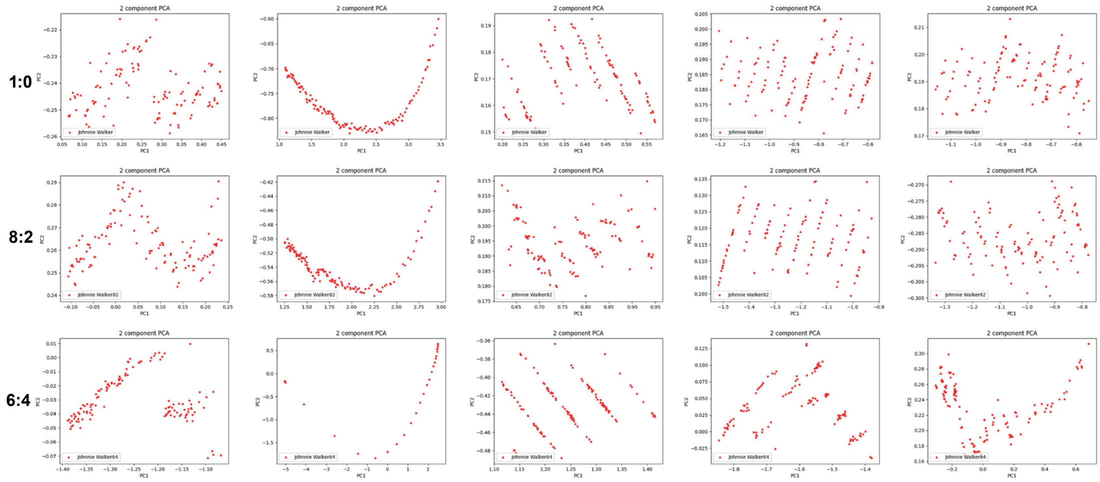


(a)



(b)

Fig. 11. (Color online) Examples of odor fingerprints of tested whiskies: (a) Jack Daniel's, (b) The Famous Grouse, and (c) Johnnie Walker.



(c)

Fig. 11. (Color online) (Continued) Examples of odor fingerprints of tested whiskies: (a) Jack Daniel's, (b) The Famous Grouse, and (c) Johnnie Walker.

4. Discussion

E-nose systems have several advantages over traditional analysis methods in detecting and classifying aroma compounds in spirits. By mimicking the human sense of smell, these systems can capture complex odor signatures with high sensitivity and repeatability. The sensor array technology used in the e-nose can detect multiple VOCs simultaneously, allowing us to build odor data for different spirit odors. This approach is particularly valuable in rapidly screening large numbers of samples and facilitates the timely identification of potentially adulterated or counterfeit products. In our experiments, the trained model demonstrated excellent performance. The CNN-LSTM model adopted in this study showed high accuracy in multiclass classification tasks, showing its effectiveness in distinguishing different whisky samples. All experiments using the algorithm yielded very good results, with accuracy ranging from 93% to 94% depending on the type of whisky. The algorithm used almost always has an accuracy of over 90%, and for several of the whisky types tested, the accuracy was as high as 94%. The results are excellent and critical to ensuring product authenticity and purity, especially when dealing with increasingly sophisticated adulteration techniques. The impact of this work is critical to safeguarding consumer health and maintaining the integrity of the spirits market. However, although the results of this study were promising, further expansion of the dataset by increasing sample size is needed to enhance the robustness and generality of the model. Special care must be taken when adjusting concentration. We found that in samples with high water content, slight ratio abnormalities can cause significant differences in the values collected by the sensors. These experimental procedures are crucial to addressing potential biases and ensuring system reliability across different spirit types and production methods. In addition, the application of this e-nose and machine learning approach to spirits can provide valuable experience for other food and beverage industries and help to comprehensively strengthen food safety measures.

5. Conclusions

In this study, we proposed a method that combines e-nose technology with machine learning techniques to verify the purity of specific aroma compounds in whisky. By utilizing e-nose technology that mimics human olfaction coupled with advanced AI algorithms, we established a reliable approach to analyzing and classifying the inherent aroma characteristics of different whisky brands. During the data collection process, the e-nose system effectively collects the transient responses of multiple sensors to the VOCs emitted by whisky samples. The collected data provides comprehensive insights into aroma characteristics, laying the foundation for further analysis using complex machine-learning techniques. Several models were tested for their ability to classify whisky aroma profiles accurately. Among the models evaluated—RNN, CNN, LSTM, and CNN-LSTM—the CNN-LSTM model outperformed the others, achieving the highest accuracy and lowest loss. This model demonstrated robust performance, showcasing its potential in verifying alcohol purity.

Additionally, tests conducted on pure whisky and whisky mixed with water samples demonstrated the system's ability to distinguish between different alcohol concentrations. The model, trained on pure whisky data, effectively classified blended samples, providing valuable insights into alcohol purity and its variations. The collected odor characteristics were also visualized to compare and distinguish different samples, facilitating precise control over alcohol-to-water ratios. This approach can also create digital archives of specific types of spirits, ensuring consistency and quality in whisky production and consumption. While the e-nose system accurately classified whisky samples diluted with water, this study was primarily focused on water content as the sole diluent. Consequently, to enhance the system's classification performance, purity recognition within water-diluted samples should be improved. In future research, the dataset should be extended to include samples with various common adulterants, such as methanol or added flavor compounds, to realistic broader applicability in verifying authenticity and detecting potential adulterants beyond water. Expanding the range of impurities would enable a more comprehensive assessment of the system's robustness in broader scenarios of spirits authenticity recognition. Throughout the study, various challenges were encountered and addressed, including the impact of the sample container design on the data collection and the optimization of the data collection duration. By overcoming these challenges, the proposed system and method are able to offer an efficient, noninvasive way to ensure the purity of whisky and improve the accuracy of alcohol measurement in the restaurant industry.

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