Impact of Drift Factor on Feature Optimization in Electronic Nose Detection Systems

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Abstract:
The electronic nose, a vital tool for olfactory detection in non-destructive testing (NDT), plays a critical role in mimicking human olfaction. However, its performance is frequently hampered by drift phenomena, including sensor degradation due to environmental variations and olfactory fatigue from prolonged usage. While the impact of drift on electronic nose performance is well-documented, its influence on feature optimization remains underexplored. This study introduces a novel perspective: drift factors not only disrupt sensor readings but also significantly influence the feature optimization process and subsequent drift compensation. To investigate, we focused on temperature and humidity—two predominant environmental drift factors. Experimental results confirmed that drift factors substantially affect feature optimization, demonstrating a positive correlation between sensor score concentration and classification accuracy. We employed an innovative quadratic feature optimization method to mitigate drift effects during feature optimization, enhancing the electronic nose's drift resilience. The unweighted quadratic feature optimization method emerged as the most effective, achieving a 100% recognition rate on the training set and 96% on the test set. These results highlight the method's potential to significantly enhance drift resistance in electronic nose systems. This study provides insights into the interplay between drift factors and feature optimization, offering a robust framework for advancing electronic nose technology.

Keywords: electronic nose; drift compensation; feature optimization; random forest; artificial neural networks

1. Introduction:

Non-destructive testing (NDT) technologies have revolutionized agricultural product quality assessment by providing efficient, accurate methods to evaluate intrinsic characteristics without causing physical damage. Among these, electronic nose (e-nose) technology has emerged as a powerful tool, utilizing volatile organic compounds (VOCs) emitted by agricultural products to assess quality. The e-nose system comprises two core components: a gas sensor module and a data processing module. Its working principle mimics the olfactory system of living organisms, with gas sensors reacting to specific gas molecules and producing potential changes that the data processing module interprets into quantifiable gas concentration metrics.

Electronic noses have gained traction not only in agriculture but also in industries like food safety, pharmaceuticals, and environmental monitoring, owing to their versatility and sensitivity. Within agriculture, e-noses are extensively used to evaluate parameters such as the quality, ripeness, and freshness of crops. For example, they have been employed to analyze aroma profiles in tea, jujube, and other crops where VOCs like alcohols, aldehydes, and ketones serve as critical indicators. Tea, in particular, offers a rich test case due to its diverse types, fermentation methods, and varying storage conditions, which produce distinct VOC profiles. Using an e-nose, these aromatic compounds can be detected and analyzed without compromising the physical structure of the sample, making it a valuable tool for quality control.

Despite their advantages, e-noses are prone to drift phenomena that degrade sensor performance over time. Drift arises from factors such as sensor aging, olfactory fatigue, and environmental conditions like temperature and humidity. These issues compromise detection accuracy and operational stability, presenting a significant challenge in practical applications. Studies have shown that ambient temperature and humidity are key contributors to drift. Current drift compensation strategies primarily involve either improving sensor materials or implementing mathematical modeling techniques. Material-based enhancements, while promising, often face challenges in scalability and cost-effectiveness.

As a result, mathematical modeling has emerged as a more practical approach for drift compensation, allowing researchers to improve sensor performance without altering existing hardware.

Several innovative methods have been proposed to address drift. For instance, neural network-based domain adaptation techniques have demonstrated effectiveness in correcting distortions caused by drift, while methods such as collar reconstruction limit learning machines and nonlinear feature extraction have shown promise in enhancing robustness against environmental variations. However, while extensive research has focused on how drift impacts overall sensor performance, the influence of drift on feature optimization processes has received comparatively little attention.

This study seeks to bridge that gap by investigating how drift factors affect feature optimization in e-nose systems and proposing methods to mitigate these effects. Specifically, we aim to:

1. Process datasets to visualize the impact of drift on feature optimization, evaluate sensor performance under various conditions, and identify patterns in drift behavior.
2. Introduce a secondary feature optimization method that minimizes drift interference and establish a positive correlation between sensor score concentration and classification accuracy.
3. Evaluate and identify the optimal combination of feature optimization and compensation methods to significantly enhance the drift resistance of electronic nose systems.

Through these steps, our research contributes to advancing e-nose technology by improving its resilience to drift, paving the way for more reliable applications in agriculture and beyond.

One notable direction in drift compensation involves domain adaptation, where models are trained to adapt to new environments by transferring knowledge learned from a source domain to a target domain. This approach has been successfully implemented in several studies, with researchers employing neural networks and other machine learning techniques to correct for drift-induced distortions. Other methods focus on improving the feature extraction process, allowing the system to extract more stable and robust features that are less sensitive to drift. Despite the advancements in drift compensation, much of the research has primarily focused on improving overall sensor performance without considering how drift may specifically affect the feature optimization process.

This study aims to address this gap by focusing on the effect of drift factors on feature optimization in e-nose systems. Feature optimization plays a critical role in improving the accuracy and efficiency of the sensor data processing module. The process involves selecting and refining the most relevant features from the sensor data to enhance classification performance. However, drift can introduce noise into this process, making it harder to identify the true features of interest. By exploring the impact of drift on feature optimization and proposing effective compensation methods, this study aims to improve the drift-resistance of e-nose systems, thus enhancing their reliability in practical applications.

The study is structured as follows:

1. **Dataset Processing and Drift Visualization:** First, we process the dataset to visualize how drift factors affect feature optimization. By comparing sensor performance under various environmental conditions, we aim to uncover patterns and relationships that shed light on the role of drift in feature optimization.
2. **Feature Optimization and Sensor Score Concentration:** Next, we explore how secondary feature optimization can mitigate the impact of drift. We introduce a new hypothesis that suggests a positive relationship between sensor concentration and the correct classification rate, supporting the importance of proper feature optimization.
3. **Optimal Compensation Methods:** Finally, we compare different combinations of feature optimization techniques and compensation methods to identify the best approach for improving drift resistance. Through this process, we aim to provide valuable insights into improving e-nose technology, making it more robust for real-world applications.

In conclusion, this study not only contributes to the understanding of how drift factors influence feature optimization in electronic noses but also offers practical solutions to improve the drift resistance of these systems. These findings could significantly enhance the applicability and reliability of e-nose technology, particularly in industries like agriculture, where product quality control is paramount.

2. Materials and Methods

2.1 Experimental Apparatus and Experimental Samples

In this study, the temperature and humidity conditions were precisely controlled to simulate various environmental settings and assess their influence on the tea samples. A small temperature and humidity chamber, specifically the

DHTHM-27-O-P-ES model from the DHT® brand (Shanghai, China), was used for this purpose. This chamber allowed us to maintain consistent environmental conditions throughout the experiment.
The experiment was designed to evaluate the tea samples under five distinct temperature gradients: 5°C, 15°C, 25°C, 35°C, and 45°C. These temperatures were chosen to cover a broad range of potential storage or brewing conditions. The relative humidity, which is the ratio of the air's vapor pressure to the saturated vapor pressure, was maintained at a consistent level of 60 ± 5%. Relative humidity is often preferred over absolute humidity in environmental control experiments due to its direct influence on the perceived air quality and the potential to impact chemical processes in the samples.

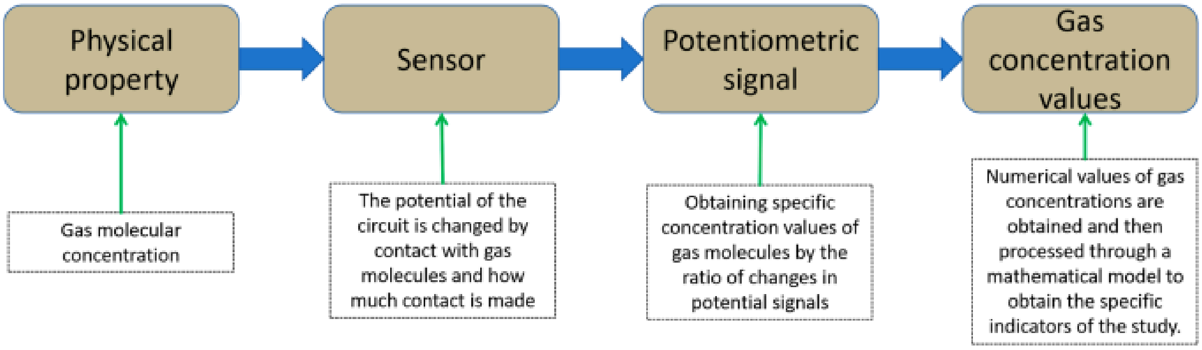

Figure 1. Schematic diagram of the electronic nose workflow.

In addition to the temperature control, the study further investigated how varying levels of humidity would affect the tea samples. The relative humidity levels were specifically set at 35%, 50%, 65%, 80%, and 95%, with the temperature consistently held at 25 ± 1°C. These humidity settings were chosen to reflect common environmental conditions that tea may experience during storage, packaging, and consumption.
Five different tea varieties were selected for this experiment: **Huangshan Maofeng**, **Yinghong No. 9**, **Xihu Brand**, **Biluo Brand**, and **Xinyang Maojian**. These teas were selected to represent a broad range of flavor profiles and chemical compositions, offering a comprehensive dataset for evaluating the environmental impact. Each tea variety was replicated 20 times per temperature or humidity condition. However, during the course of the experiment, data anomalies were observed in two samples: Huangshan Maofeng under 95% humidity and Biluo Brand under 65% humidity. These samples were removed from the dataset to ensure the integrity of the experimental results.
The main instrument used in this study to gather data was a portable **PEN3 electronic nose** (Airsense, Germany), which is a widely recognized tool in sensory analysis laboratories for identifying and analyzing the gas fingerprints emitted by various substances, such as tea. The electronic nose consists of a gas sensor module and a data processing module. The gas sensor detects target gas molecules by measuring the changes in electrical potential on the sensor surface when the molecules come into contact with it. This change in potential is then processed by the data processing module, which converts it into specific concentration values that can be analyzed.
The electronic nose employed ten different gas sensors, each designed to detect different types of gases emitted by the tea samples. The sensors were calibrated to ensure accurate detection of the gas particles associated with the teas' chemical characteristics. The experiment was conducted with several specific parameters: the gas flow rate was set to 190 mL/min, and a sampling cleaning time of 60 seconds was applied before each sampling session. The data acquisition interval was 1 second, while the sensor zero waiting time was set to 10 seconds to stabilize the sensor readings. Each tea sample was fed into the e-nose for 5 seconds, and the total sampling and analysis time was 60 seconds per sample. The data for each sample were collected and processed at the 57th second of the sampling period, ensuring that each data point represented a consistent and accurate reading.
These detailed environmental control procedures and experimental setups allowed us to rigorously assess the impact of temperature and humidity on the emission profiles of the tea samples, providing insights into the sensory properties of tea under varying storage conditions. The use of the electronic nose, combined with careful control over environmental parameters, enabled the extraction of reliable data that can be further analyzed to understand how different environmental factors influence the volatile compounds in tea.
In this experiment, 1 g of the tea sample was precisely weighed using an electronic balance and placed into a 100 mL beaker. The beaker was then placed inside a temperature-controlled test chamber. To maintain a constant environment, the chamber was equilibrated to the desired temperature and humidity levels, with a stabilization period of half an

hour before starting the analysis. After this period, the beaker was removed, and a double layer of plastic wrap was used to seal its opening, preventing any further interaction with external factors. The headspace sampling technique was then employed to collect the VOCs emitted by the tea sample for analysis.

To simulate the real-world conditions of agricultural product testing more accurately, the experimental setup included controlling not only the temperature and humidity of the incoming detection gas but also the environmental conditions where the agricultural products were stored and tested. This approach aimed to mimic the actual detection environment of the electronic nose, ensuring that the results of the experiment were as credible and representative of real-world scenarios as possible.

2.2. Machine Learning Mathematical Models

For data processing and analysis, we selected JMP PRO 16.1.0, a comprehensive software platform known for its robust statistical and machine learning tools. Among the various algorithms available, we chose the Random Forest (RF) classification model due to its effectiveness in handling complex datasets and its suitability for sensor evaluation and feature importance analysis.

Random Forest is an ensemble machine learning technique that builds multiple decision trees and merges them to provide more stable and accurate predictions. This approach is particularly valuable when working with unbalanced datasets, as the random sampling strategy used in Random Forest helps to reduce errors and improve model stability. Additionally, Random Forest has a built-in feature selection process, which allows it to automatically evaluate the importance of each sensor in the dataset. This is a crucial advantage for our experiment, as one of the main objectives was to assess the sensor's performance in terms of its contribution to the classification process.

In this study, we configured the Random Forest parameters as follows: the number of trees in the forest was set to 100, 200, or 500; the splitting criteria were chosen as Gini Index and Entropy; the maximum depth of the trees was limited to 14; the minimum number of samples required to split a node was set to 5; and the sampling method used was bootstrap sampling. These settings were optimized through repeated debugging, ensuring that the model was both accurate and stable. Furthermore, the training and validation dataset were split in a 4:1 ratio to maintain a robust and reliable model performance.

In addition to Random Forest, we also incorporated an Artificial Neural Network (ANN) as a classical approach for drift compensation, allowing for a direct comparison of the advantages of secondary feature optimization. Neural networks, inspired by the structure and function of biological neurons, are capable of modeling complex, nonlinear relationships. In this experiment, the ANN consisted of an input layer, two hidden layers, and an output layer. The first hidden layer contained 3 neurons, while the second hidden layer was configured with 20 neurons. The network was designed to model and predict drift-induced variations in sensor data, allowing for the compensation of these drifts and improving the overall detection performance of the electronic nose.

The integration of both Random Forest and ANN models allowed for a comprehensive analysis of the feature optimization process and drift compensation, providing valuable insights into the performance improvements achievable by secondary feature optimization and other compensation techniques.

2.2. Machine Learning Mathematical Models

In this study, we employed **JMP PRO 16.1.0** as the software platform for data processing, utilizing advanced machine learning models for feature selection, classification, and performance evaluation of the electronic nose. The two primary machine learning techniques applied were **Random Forest (RF)** and **Neural Networks**, each serving specific roles in the experiment.

Random Forest Classification Model

Random Forest (RF) is a widely-used, robust machine learning algorithm that operates by creating an ensemble of decision trees, each trained on a random subset of the data. This method is known for its high accuracy and stability, especially when dealing with unbalanced datasets, which is a common issue in sensor data classification. We chose Random Forest due to its ability to evaluate the importance of various features (in this case, sensor data), which is critical for understanding the relative contribution of each sensor to the overall classification process.

The parameters chosen for the Random Forest model in this study were:

- **Number of Trees**: 100, 200, and 500 trees were tested to determine the optimal number of trees that provided stable and accurate predictions.
- **Splitting Criteria**: Both **Gini impurity** and **Entropy** were used to assess the quality of the splits in the decision trees.

- **Tree Depth**: A maximum depth of 14 was set for each tree to prevent overfitting while allowing enough complexity to capture the relationships in the data.
- **Minimum Samples for Node Split**: The minimum number of samples required to split a node was set to 5, ensuring that the decision tree did not create overly granular splits.
- **Sampling Method**: The **bootstrap sampling method** was used for training the decision trees, which helps ensure the stability of the model by randomly sampling subsets of the data for each tree.

These settings were fine-tuned through repeated debugging to ensure optimal performance. Additionally, the **training/validation set ratio** was adjusted to 4:1, with 80% of the data used for training and 20% for validation.

Random Forest was particularly useful in this study as it allows for intuitive evaluation of feature importance, which was essential for assessing the role of each sensor in the overall classification process. This approach helped identify which sensor data contributed most to the classification task, providing insights into the electronic nose's sensor performance under various environmental conditions.

Neural Network Compensation Model

To further optimize the results and account for potential drift or bias in the electronic nose's sensor readings, a **Neural Network** model was incorporated. Neural networks are inspired by biological neurons and are adept at learning complex, nonlinear relationships within data. In this experiment, the neural network model was used for compensating the performance of the electronic nose by predicting and correcting sensor data that may have been affected by temperature and humidity variations.

The neural network model used in this study consisted of three layers:

- **Input Layer**: The input layer took in the raw sensor data collected under various temperature and humidity conditions.
- **Hidden Layers**: The first hidden layer contained 3 neurons, while the second hidden layer was larger, with 20 neurons. This structure allowed the model to capture complex interactions between the input features.
- **Output Layer**: The output layer provided the predictions or compensation values for the sensor data, which were used to adjust the readings for any detected biases or drift.

The neural network model was trained using the classification results from the Random Forest model. The data with higher classification accuracy were used to train the neural network, aiming to improve the compensation effect. Conversely, the data with lower classification performance were fed into the neural network for compensation and convergence, allowing the model to predict and adjust the drift data. This compensation step helped refine the sensor readings by adjusting for inconsistencies caused by environmental factors.

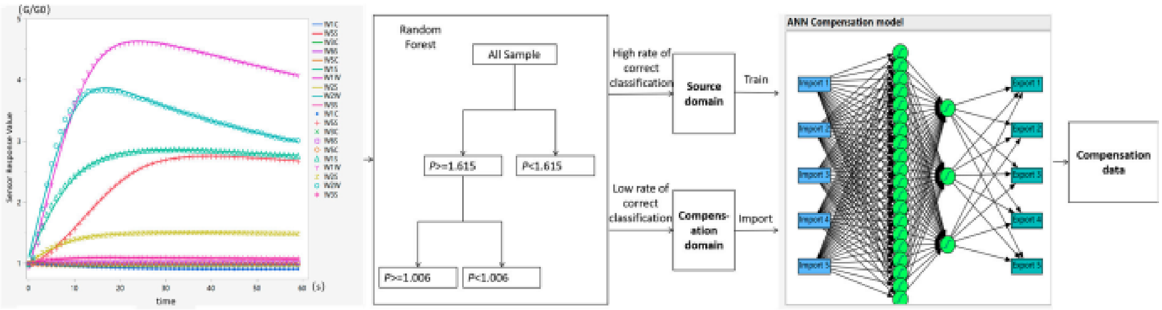

Figure 2. Neural network compensation flowchart.

The neural network model performed the crucial task of **data convergence and prediction**, compensating for any inaccuracies in the sensor data due to varying temperature and humidity conditions. After compensation, the data were used for secondary feature optimization and compared with the original uncorrected data to evaluate the improvements in classification accuracy and sensor performance.

Compensation Process

The compensation process is depicted in **Figure 2** (referenced in the original text). In summary, the data were first processed through Random Forest for feature selection and classification. The resulting classified data with higher accuracy were then used to train the neural network compensation model. The neural network predicted and adjusted the data that exhibited lower classification performance, resulting in compensated data that were subsequently used for further analysis and optimization.

By combining both Random Forest and Neural Networks, this study was able to not only classify and optimize the sensor data but also correct for any biases introduced by environmental conditions, thus improving the overall accuracy and reliability of the electronic nose system.

2.3. Data Processing Procedures

In the drift compensation process for electronic noses, feature optimization is typically the most commonly applied method. However, since drift can significantly influence the optimization of features, we propose a secondary feature optimization process. This approach aims to minimize the impact of drift factors on the electronic nose's performance by using a reduced number of sensors while still achieving accurate results.

As illustrated in Figure 3, the compensation methodology employed in this study is inspired by the work of Qiao Wenchao et al. [23], who utilized a Backpropagation (BP) neural network for sensor compensation. In our experiment, the process starts with the optimization of the original sensor data collected by the electronic nose. The first step involves using the Random Forest algorithm to assess the performance of various sensors. This model outputs sensor scores, which are then subjected to the forward selection method. Forward selection is a feature selection technique where the most relevant sensors are identified and selected iteratively based on their contribution to the model's performance.

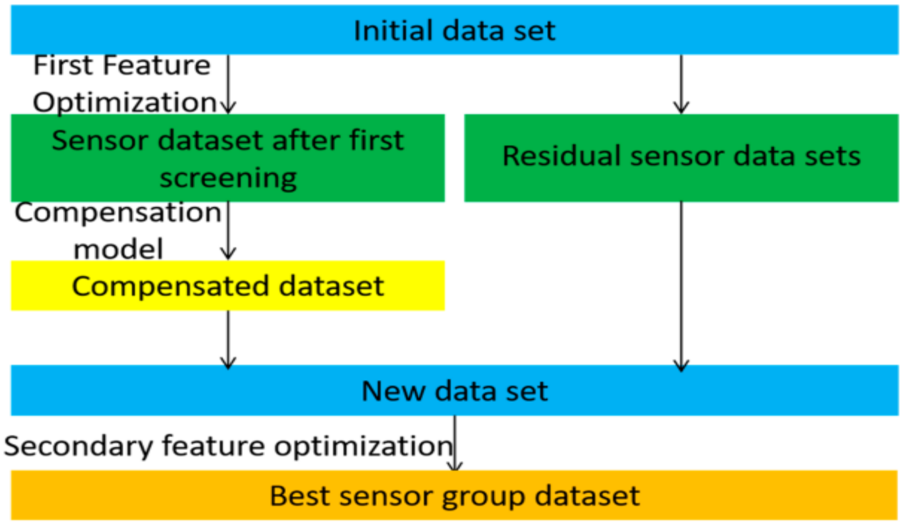

Figure 3. Flowchart for differentiation and compensation of datasets.

After this first feature optimization step, the resulting optimized dataset is passed through an artificial neural network (ANN) for further compensation. The ANN is used to model and correct the drift effects in the sensor data, improving the consistency and reliability of the measurements. The compensated dataset, now adjusted for drift, is then merged with the original dataset, which consists of the remaining sensors from the first optimization. This combined dataset forms the input for the second feature optimization stage.

The second feature optimization aims to refine the selection of sensors even further, ideally resulting in a smaller and more efficient subset of sensors that minimizes the drift effect on the electronic nose's performance. The final step involves evaluating the classification accuracy of the optimized dataset in categorizing tea samples. By comparing the classification rates before and after the secondary optimization, we can assess the effectiveness of the proposed approach in improving the electronic nose's drift-resilience and overall performance.

In summary, the approach of secondary feature optimization, coupled with sensor compensation through the use of Random Forest and ANN models, is shown to be effective in reducing the impact of drift factors. This leads to a more robust and accurate electronic nose system capable of performing better under varying environmental conditions.

3. Results and Discussions

3.1. Drift of the Electronic Nose

In the context of drift compensation for electronic noses, it is common to study the impact of drift by controlling only the humidity or temperature of the incoming gas. However, this approach often does not accurately reflect real-world detection scenarios. A major issue arises when the sample's temperature and humidity are considered separately from the detection conditions. Specifically, the temperature of the sample is influenced by the difference between the sensor's operating temperature and that of the sample, while the humidity may differ between the sample's environment and the detection conditions【17】. These discrepancies necessitate that the compensation module account for the interaction between both temperature and humidity factors, further complicating the calibration process.

To address this, we adopted a more realistic approach by controlling both the sample and detection environments to better simulate the operational conditions of an electronic nose during actual use. This method ensures that the sensor operates within conditions that mirror those encountered in real detection scenarios, allowing for more accurate and reliable compensation.

Figure 4 clearly illustrates the effect of drift on the electronic nose under various detection conditions. The degree of data centralization for the same tea sample reflects the extent of the drift effect; more centralized data points indicate minimal drift, while greater dispersion suggests a significant drift impact. Drift leads to variability in sensor readings, which compromises the accuracy of classification by the electronic nose. On the other hand, a higher degree of overlap in the data at the same temperature and humidity levels signals increased difficulty in distinguishing between the tea samples.

More specifically, the results in Figure 4 demonstrate that higher humidity levels lead to more dispersed data points, a finding consistent with the observations of Jiwon et al. [24]. Conversely, lower humidity conditions show higher data overlap, which may indicate more challenging classification tasks due to less distinct separation between different tea types. Temperature conditions also played a crucial role, with higher temperatures causing more dispersion in the data from the tea samples. This suggests that drift, driven by both temperature and humidity, introduces considerable challenges in distinguishing between tea samples, further complicating the classification process.

3.3. Electronic Nose Compensation

In this study, we employ an artificial neural network (ANN) for the compensation of the electronic nose, a well-established machine learning algorithm that has shown promising results in compensating for the drift in gas sensor data. Artificial neural networks have been widely used in sensor data compensation, with studies like those conducted by Nenova et al. [25] demonstrating their effectiveness. The primary goal of this research is to investigate the influence of drift factors on the feature optimization process of the electronic nose. To achieve this, we use the ANN model to compare the sensor data before and after feature optimization, aiming to understand the specific impact of drift on the performance of the electronic nose.

3.3.1. Determining the Scope of Compensation

Not all environmental conditions require compensation in the case of the electronic nose, as compensating for every variation could lead to overfitting, which in turn may reduce the detection efficiency of the sensor system. To avoid this, we utilized the random forest model to separately classify the results under each experimental condition and evaluated the classification accuracy for each gradient. This step is essential in identifying which drift factors are significant enough to warrant compensation and which ones could be left unaddressed without negatively affecting the performance of the electronic nose. By carefully selecting which environmental conditions to compensate for, we ensure that the model maintains its robustness while avoiding unnecessary complexity or loss in detection efficiency.

3.4. Comparison of Secondary Feature Optimization and Compensation Methods

In this experiment, we aimed to distinguish the results of the secondary feature optimization and to directly compare the effect of different processing methods on the anti-drift performance of the electronic nose. To achieve this, three distinct groups were used for comparison, based on the classification correctness before and after compensation:

- **Group 1: Single Feature Optimization Compensation** – This group undergoes a one-time feature optimization without any secondary processing.
- **Group 2: Unweighted Secondary Feature Optimization** – This group compensates the data by combining the first feature optimization (using uncompensated original data) with a new dataset that undergoes secondary feature optimization.
- **Group 3: Weighted Secondary Feature Optimization** – This group follows the second group's methodology but additionally applies a weighting process to the compensated data, giving preference to the compensated sensor data set for feature optimization.

Table 5 below summarizes the comparison of these groups:

Experimental Condition	Training Set Classification Correctness	Validation Set Classification Correctness	Compensation Status	Number of Feature Optimizations	Weighted State	Number of Sensor Arrays

35% RH	92%	76%	Before compensation	--	--	10
50% RH	96%	76%	Before compensation	--	--	10
65% RH	89.3%	88%	Before compensation	--	--	10
45°C	97.3%	80%	Before compensation	--	--	10
35% RH	97.3%	84%	After compensation	1	--	5
50% RH	88%	92%	After compensation	1	--	5

Figure 4. Compensated Sensor Score Diagram: In this figure, the "*" symbol in the upper right corner of the sensor indicates that the sensor data has undergone compensation. Uncompensated raw data is not marked with this symbol.
Upon comparing the data from the three groups, the results of the secondary feature optimization show a significant improvement in the classification performance of the electronic nose. Specifically, the training set results post-secondary optimization show better performance than the primary feature optimization, and the validation set shows an 8% improvement in the 45°C group, reaching a classification correctness of 96%. This indicates that secondary feature optimization effectively enhances the robustness and anti-drift capabilities of the electronic nose.

When comparing the weighted and unweighted secondary feature optimization groups, the results are quite similar, with the unweighted group showing slightly better performance in the training set. However, the unweighted group achieves this with fewer sensor arrays, making it more efficient. This is consistent with the sensor scores from the quadratic feature optimization, where a considerable number of sensors show no effect on classification and obtain a score of zero, while some compensated sensors still contribute to the classification. Therefore, we conclude that the **unweighted quadratic feature optimization grouping** is the optimal choice, as it effectively improves the correct rate of tea classification and presents a strong compensation effect.

In summary, the secondary feature optimization process, particularly the unweighted version, significantly enhances the classification accuracy of the electronic nose, making it a more robust and drift-resistant tool for tea classification

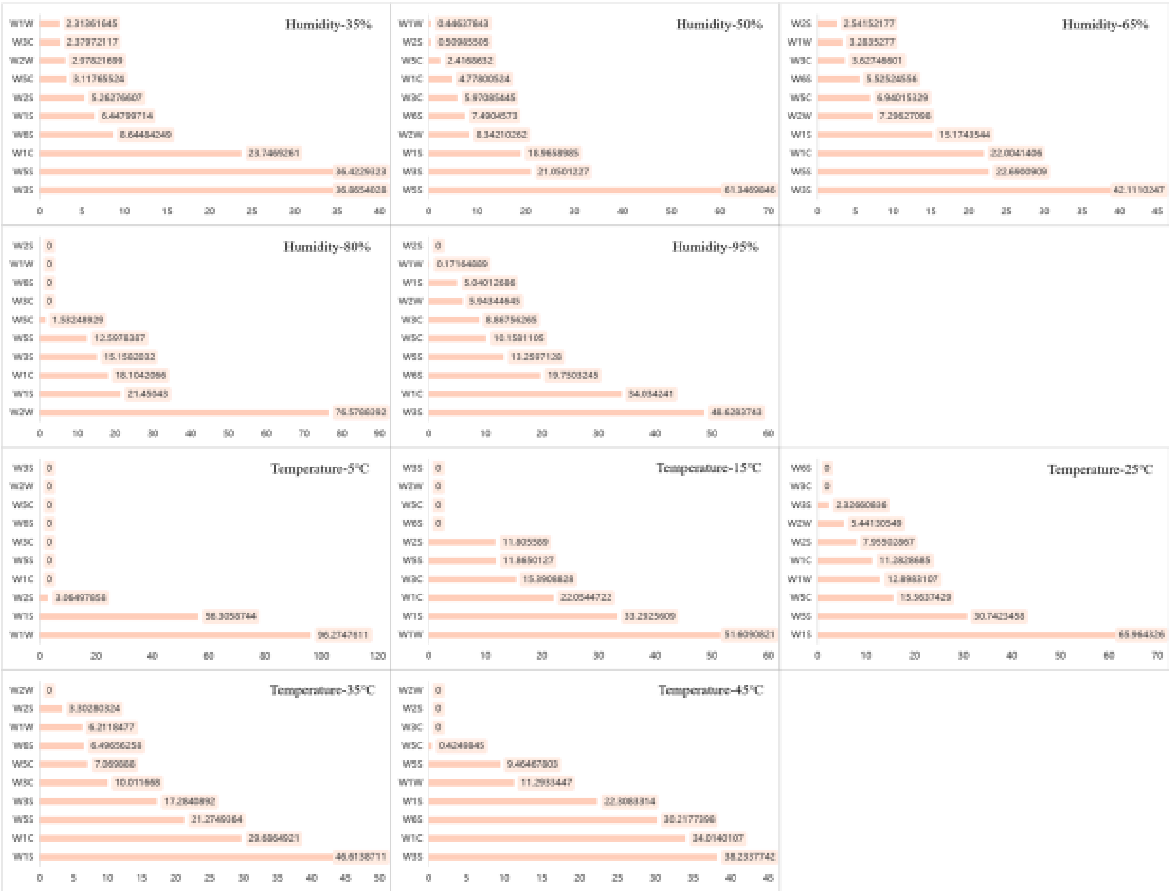

Figure 5. Plot of sensor scores for different experimental conditions.

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4. Conclusions

This study explores the impact of drift factors on the electronic nose (e-nose) system, specifically how these factors influence its feature optimization module. We began by conducting a categorical analysis of datasets collected under various temperature and humidity conditions, focusing on comparing sensor scores in these differing environments. This analysis aimed to define the range of compensation required and to identify the specific effects of drift factors on the feature optimization process. The results indicated significant variations in classification effectiveness, the degree of drift impact, and sensor scores across the experimental conditions. These findings emphasize the necessity of targeted compensation strategies for specific environmental conditions and underscore the importance of tailored treatment for the feature optimization module.

Additionally, we observed a positive correlation between sensor score concentration and the classification performance of the e-nose, with this relationship being validated by comparing sensor scores before and after compensation. To address the drift's impact on the feature optimization process, we introduced a compensation method for secondary feature optimization. This method builds upon existing strategies, aiming to further enhance the robustness and anti-drift capabilities of the e-nose. The results of this compensation approach were promising, as it improved the classification accuracy of the training dataset to 100%, while the test set accuracy reached 96%, both demonstrating excellent performance.

This study contributes to the relatively limited body of research on the effects of drift factors on feature optimization modules, offering a new avenue for improving the performance and drift resistance of e-nose technology. Our work lays the foundation for more stable and reliable e-nose systems, which are essential for real-world applications in complex and dynamic environments. Ultimately, this research provides valuable insights for advancing the e-nose's technical capabilities, ensuring its reliability and accuracy in practical, fluctuating conditions.

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