

# *A Review of Electronic Nose-Based Quality Assessment Techniques for Amomum Villosum*

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**Abstract:** Amomum villosum, a widely utilized bulk medicinal herb, has significant market demand. However, the quality of commercially available Amomum villosum is currently inconsistent. Electronic nose technology, an emerging artificial intelligence sensory technology, offers several advantages, including rapidity, non-destructiveness, intelligence, objectivity and accuracy in odor recognition. This technology has the potential to enhance the quality assessment of Amomum villosum. This study reviews existing research on the quality assessment techniques of Chinese herbal medicines, with a particular focus on Amomum villosum, utilizing electronic nose technology. The research on drift compensation associated with electronic noses is also summarized. and this study proposes that the drift problem can be mitigated by employing online compensation methods based on active learning, which aims to improve odor recognition capabilities and detection accuracy. This study is able to serves as a reference for future research on the quality assessment technology of Amomum villosum.

**Keywords:** Quality assessment of Amomum villosum, Electronic nose, Deep learning, Active learning, Online drift compensation

## 1. Introduction

Amomum villosum, the dried mature fruit of Amomum villosum Lour., Amomum villosum Lour. var. xanthioides T.L. Wu et Senjen, or Amomum longiligulare T.L. Wu, belongs to the ginger family (Zingiberaceae) [1]. Native to Yangchun, Guangdong, it is now distributed in Fujian, Guangdong, Guangxi and Yunnan, and is one of the ‘Four Great Southern Medicines’ in China. Amomum villosum holds both aesthetic and medicinal significance. It is utilized in traditional Chinese medicine, serving as an ingredient in numerous cosmetic products, and is a fundamental component in various pharmaceutical formulations. Amomum villosum contains volatile oils, which have a complex composition that includes limonene, linalool, bornyl acetate, and other components [2].

As a widely used medicinal herb, Amomum villosum is in high commercial demand; however, the quality of available products is often inconsistent, leading to the simultaneous sale of both adulterated and authentic products. The distinctive aromatic properties of the volatile oils found in Amomum villosum serve as the basis for commonly employed quality testing techniques for this herb. These methods include traditional olfactory identification, gas chromatography, sensor detection, infrared gas analysis, and other odor detection techniques [3]. These determination methods have their own advantages, however, these traditional detection techniques still have the

disadvantages of low detection efficiency, single component detection, and insufficiently comprehensive quality evaluation.

Nowadays, with the development of artificial intelligence technology, artificial intelligence sensory technology has blossomed in various aspects. Among them, electronic nose (e-nose) plays an important role in many fields by virtue of its fast, non-destructive, intelligent, objective and accurate features in odor discrimination [4]. While these approaches offer certain advantages, they also present drawbacks, such as low detection efficiency, the ability to detect only single components, and a lack of comprehensive quality evaluation.

This study presents a review of existing research on the quality assessment technology for Chinese herbal medicines, especially for *Amomum villosum*, utilizing e-nose technology. Furthermore, in light of recent advancements in deep learning, this study proposes the implementation of online compensation methods based on active learning to enhance the efficiency of quality assessment for *Amomum villosum*.

## **2. Research on quality assessment method of Chinese herbal medicine based on e-nose**

### **2.1. E-nose technology**

The e-nose is an electronic system designed to replicate a bionic sense of smell. It is also known as an intelligent odor sensor, odor fingerprint detector, odor scanner, or olfactory simulator. This system, which is an electronic olfactory sensing technology, combines applied pattern recognition technology and gas sensor arrays from various fields, including chemistry and computer science, to emulate the mammalian olfactory process [4]. A typical e-nose comprises three main components: an gas sensor array, a signal processing system, and a pattern recognition system [4]. The gas sensor converts the chemical action of various odor molecules on its surface into measurable electrical signals. These signals are subsequently processed by a signal preprocessing system, which generates odor signals through feature extraction and other relevant processing techniques. The pattern recognition system identifies the processed odor signals using multivariate statistical classification methods or neural network approaches, allowing for the identification of the odor and its conversion into a sensory evaluation index [5]. In terms of quality assessment for the detection of Chinese herbal medicines, the e-nose can be employed to establish olfactory fingerprints of herbs. This technology also aids in identifying the origin of the herbs, studying their harvesting periods, preparing Chinese herbal medicines, creating auxiliary placebos [6], identifying species, and detecting sources [7].

### **2.2. Application of e-nose technology in quality assessment of Chinese herbal medicines**

Currently, there is a growing body of research focused on the quality assessment of Chinese herbal medicines utilizing e-nose technology. Yang et al. [8] developed a classification model to analyze the response characteristics of an e-nose to *Astragalus* samples that were 2, 7, and over 10 years old. They categorize the samples based on their growth duration and examined their chemical composition and quality by applying principal component analysis and discriminant factor analysis, and the results indicated that the chemical contents of *Astragalus* samples from the same growth period were similar, while those from different growth periods exhibited significant differences. Zou et al. [3] introduced the e-nose to establish the odor fingerprints of *Fructus Amomi*. They collected 25 batches of *Fructus Amomi* samples from various varieties and origins and employed the e-nose to analyze their odors using various mathematical statistical methods. Different classifiers are developed with naive Bayes network, radial basis function, and random forest, and the positive judgment rates of the established odor discrimination models respectively validated through ten-fold cross validation and external test set validation are 78% and 84%. The results indicate that the e-nose is capable of performing qualitative analyses for distinguishing genuine and non-genuine samples of *Fructus Amomi*. Zhu et al.

[9] used the e-nose PEN3 to gather odor information from four different origins of Aromi Fructus. They constructed a BP neural network model with a three-layer structure, achieving an accuracy rate of 100% for the recognition of Aromi Fructus samples from various origins in both the training and testing sets.

Various studies have demonstrated that e-nose technology, which is a rapid, non-destructive, and highly sensitive detection method, has a wide range of applications in the rapid identification, production, and storage of Chinese herbal medicines [10]. However, e-nose technology is still under development, as aspects such as sensor technology and pattern recognition algorithms continue to have limitations. Mu et al. [11] noted that the baseline value of e-nose sensors is unstable and exhibits significant drift due to environmental factors, resulting in poor long-term stability. Additionally, the e-nose demonstrates limited selectivity and recognition accuracy when analyzing mixed gases, making it susceptible to interference from gas mixtures. Furthermore, the pattern recognition algorithms employed by e-nose primarily rely on conventional machine learning techniques, which present limitations in gas recognition and other related issues.

E-nose, such as the PEN3 e-nose used in the current detection method study, encounter challenges, including sensors that are more responsive across a broad spectrum but lack sufficient selectivity. This lack of specificity results in a diminished response to specific odors found in Chinese herbal medicines, yielding lower measurement values and leading to a less distinct characterization of odor features [12].

### **3. Active learning-based drift compensation method**

According to the aforementioned discussion, significant advancements have been made in quality assessment technologies of Chinese herbal medicines using e-nose. However, limitations in e-nose sensor technology, pattern recognition algorithms, and related research indicate that there is considerable potential for further investigation into the quality assessment of Chinese herbal medicines with e-nose. Notably, the phenomenon of ‘drift’ in e-nose during the odor recognition process presents a significant technical challenge that affects their performance.

#### **3.1. E-nose drift overview**

Including both short-term and long-term deviations which can result from various factors in sensor responses, the phenomenon of ‘drift’ in e-nose significantly impacts the accuracy and stability of e-nose systems in gas identification and detection, resulting in recognition errors and inconsistent performance. This necessitates timely compensation and corrective measures [13]. Currently, the primary research content of drift compensation methods is presented in Fig. 1 [13]. Hardware compensation and software compensation are the two primary categories of drift compensation methods [13].

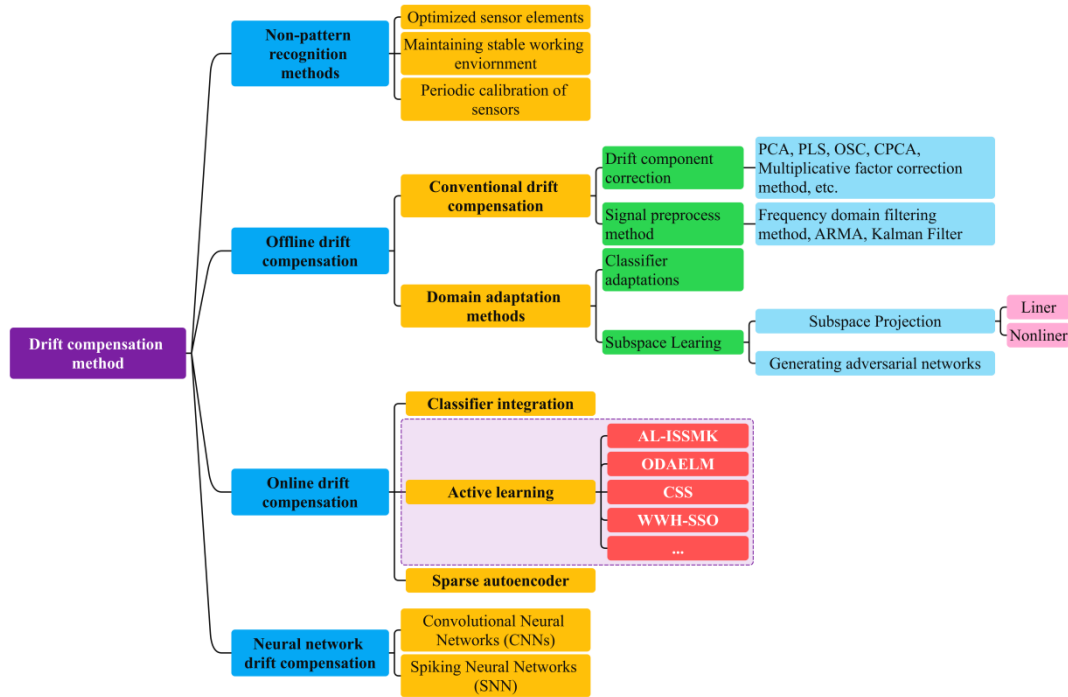


Figure 1: Primary research content of drift compensation methods [13]

Hardware compensation involves modifying the sensor hardware to mitigate drift, which may include component adjustments, stabilization of materials, and improvement in manufacturing processes. In contrast, software compensation primarily utilizes historical data models, machine learning, mathematical methods, and other algorithms to address drift during data processing. Among these approaches, software compensation is the predominant method for addressing drift. Software compensation can be categorized into two primary methods: online and offline drift compensation. Offline methods primarily include techniques based on signal preprocessing, feature transformation, and predictive model adaptation. While sensor drift can be compensated to some extent, offline methods are often impractical for real-world applications due to the need for frequent calibration, cumbersome operations, and limited adaptability. Therefore, the investigation of online compensation models is crucial for addressing e-nose drift [13, 14, 16].

### 3.2. Online active learning-based drift compensation methods

Compared to the limitations of offline compensation methods regarding real-time performance, stability, and ease of operation, online methods offer superior real-time capabilities, stability, and adaptability. Most current online drift compensation techniques are grounded in active learning algorithms, which provide the advantage of dynamically integrating new data samples and promptly updating the model to accommodate changes in data distribution [13].

Liang et al. [14] employed a when-which-how problem-based semi-supervised online method (WWH-SSO), as illustrated in Fig. 2, to update the prediction model by utilizing unlabeled samples collected during the operation of the e-nose and achieve unsupervised and online drift compensation. Tao et al. [15] proposed an online drift compensation method based on sparse autoencoders, which achieves classification accuracy comparable to, or even exceeding, that of offline drift compensation methods. This is accomplished through the feature learning capabilities of sparse autoencoders and the label discrimination of classifiers, all without relying on any samples from the target domain. A

novel active learning-based online drift compensation framework was proposed by Se et al. [16]. This framework consists of four key functions: model training, selecting the most valuable samples, model prediction and updating. In terms of both gas classification and concentration prediction task, the framework outperforms several kinds of advanced methods, including active learning instance-selection strategy on a mixed kernel framework (AL-ISSMK) [17], online domain adaptation extreme learning machine (ODAELM) [18], and classifier-state sampling (CSS) [19]. The experimental results of various methods applied in the gas classification experiment conducted by Se et al. are presented in both Fig. 3 (a) and Fig. 3 (b) [16], clearly demonstrating the impact of the framework.

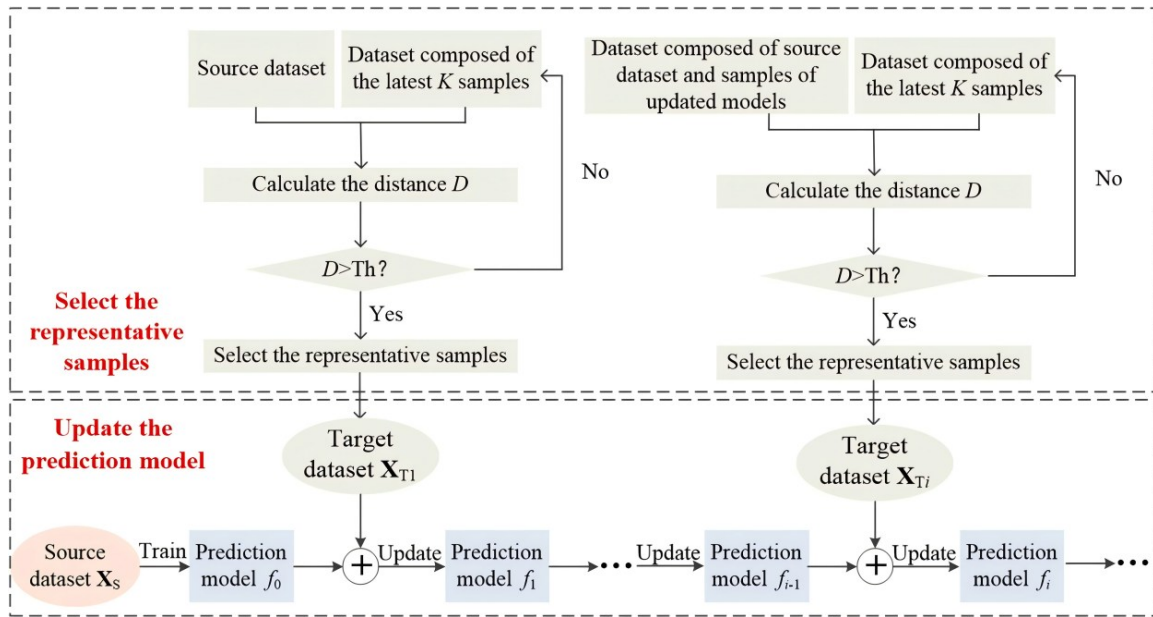


Figure 2: WWH problem-based semi-supervised online framework [14]

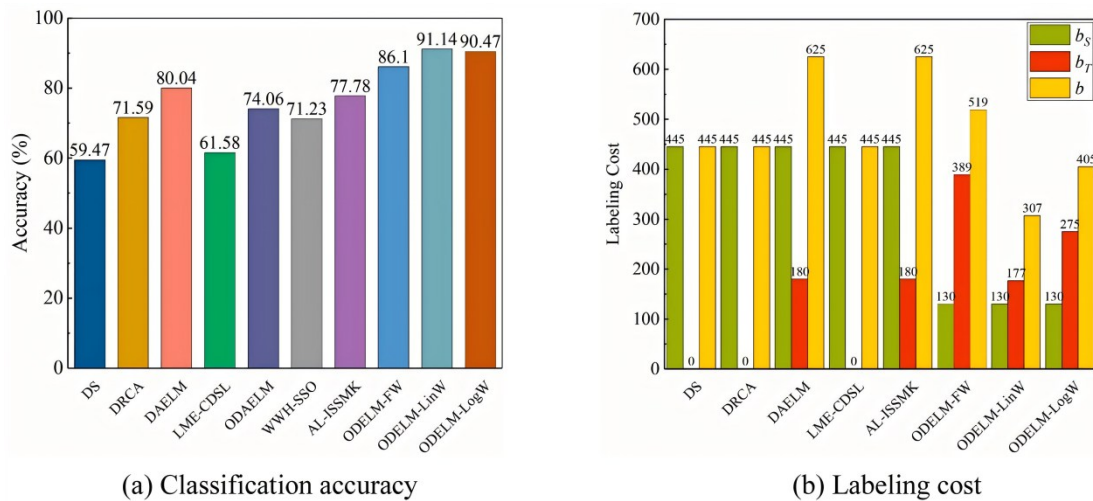


Figure 3: Experimental results of different methods for the gas classification experiment [16]

The aforementioned methods can be applied to techniques for assessing the quality of Amomum villosum. These methods provides significant advantages in real-time performance, stability, and robust self-adaptive capabilities [13]. They are able to effectively address the pronounced drift issues

of e-nose sensors, enhances the odor recognition capabilities of the e-nose, and improves both the accuracy of odor recognition and the efficiency of quality assessment for *Amomum villosum*.

#### 4. Conclusion

As an intelligent, rapid, and efficient bionic olfactory technology, e-nose technology has a wide range of applications across diverse fields, ranging from food safety to healthcare. This study reviews the research findings on e-nose technology in quality assessment technologies of Chinese herbal medicines, including *Amomum villosum*. Based on the current advancements in deep learning, this study proposes utilizing online compensation methods grounded in active learning to mitigate sensor drift in e-nose during operation. This application aims to enhance the efficiency of e-nose, improve their ability to identify odors, and increase the accuracy of odor identification, thereby optimizing the quality assessment of *Amomum villosum*. Deep learning algorithms, compared to traditional machine learning algorithms, provide significant advantages in real-time performance, stability, adaptability, and other areas. Online drift compensation methods based on active learning are particularly well-suited for practical applications of e-nose, including quality assessment of *Amomum villosum* and meat freshness assessment. However, there remains considerable space for further research into the development of online drift compensation methods. For instance, there is a scarcity of studies examining the effectiveness of these methods in addressing nonlinear drift. Future research could focus on enhancing online drift compensation techniques for nonlinear drift to improve their adaptability across a broader range of practical applications.

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