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A Review of the Application of Electronic Nose Combined with Deep Learning in Wine Quality Detection

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Abstract. Inspired by biological olfaction, the electronic nose is a modern detection instrument that mimics the structure and function of the olfactory system. It has been successfully applied in various fields, including industry and food testing. Wine is a globally beloved alcoholic beverage, and the technology used for wine quality detection plays a crucial role in ensuring the healthy development of related industries. The use of electronic noses in wine detection offers potential advantages such as rapid analysis and portability. This paper provides a comprehensive review of research on wine aroma detection using electronic noses, explores deep learning methods for processing e-nose data, and discusses the application and future prospects of combining electronic noses with deep learning in the wine industry.

Keywords: Wine detection, Odor recognition, Electronic nose, Deep learning

1. Introduction

Alcoholic beverages are among the most widely consumed drinks by humans. Among them, wine is especially popular due to its unique flavor and aroma. As early as 4000 BCE, the ancient Greeks had already mastered grape cultivation and winemaking techniques. With the advancement of technology, the techniques and demand for wine tasting have grown significantly, creating an urgent need for a scientific and reliable method to evaluate wine quality.

1.1. Overview of wine

Wine is an alcoholic beverage produced through full or partial fermentation of grapes or grape juice. It contains a certain level of alcohol and is composed mainly of water, ethanol, tannins, sugars, acids, pigments, and aromatic compounds. It is currently the most widely produced and consumed monosaccharide-fermented beverage in the world. Winemaking has a long history, and since 1892, it has evolved into a modern industrial process. Industrialization demands the standardization of the winemaking process, which in turn necessitates tools capable of conducting chemical analyses—these have become essential for automating production and ensuring consistent wine quality. Standardization requires the identification of measurable and representative indicators of wine quality. Given that the types of wine vary greatly depending on raw materials, brewing methods, and fermentation time, they exhibit distinct aroma profiles. As a result, aroma has become an effective

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indicator for evaluating wine quality. However, due to the diverse sources and compositions of these aromas—comprising roughly 800 aromatic compounds—chemical analysis becomes a formidable challenge. Using instruments that can classify wines based on their geographical origin or grape variety during the production or processing stages can aid in the standardization of wine production. These instruments provide objective measurements of wine characteristics and quality.

1.2. Traditional methods for wine quality detection and evaluation

Traditional methods for evaluating wine quality primarily include sensory evaluation and physicochemical analysis. Sensory evaluation focuses on three aspects—color, aroma, and taste—to assess wine quality. However, because it relies on human perception, it is subject to individual differences, subjectivity, and accumulated experience, which can lead to significant variation in results across evaluators. Physicochemical analysis, such as near-infrared spectroscopy, offers more objective results but typically involves complex, time-consuming, and labor-intensive preprocessing. The electronic nose, by contrast, offers high sensitivity, fast response, ease of operation, and the ability to identify various volatile compounds, making it an ideal tool for wine aroma detection and analysis. Using an electronic nose for wine aroma detection has several advantages: it is easy to operate, non-contact, non-polluting, non-destructive, and provides objective and accurate results.

2. Application of electronic nose in wine detection

2.1. Principles and classical methods of the electronic nose

An electronic nose is a bionic olfactory sensing system that detects and identifies gases or volatile organic compounds (VOCs) by mimicking the biological olfactory mechanism. It mainly comprises three core components: a sensor array, a signal processing module, and a pattern recognition system. The sensor array typically consists of chemical sensors with cross-sensitivity characteristics [1], such as metal oxide semiconductors (MOS), conductive polymers, quartz crystal microbalances (QCM), or surface acoustic wave (SAW) sensors. These sensors exhibit different adsorption-desorption responses to specific gas molecules, thereby generating multidimensional response signals. The signal processing module converts raw electrical signals into standardized data matrices through processes like noise reduction, baseline correction, and feature extraction. The pattern recognition system maps the odor features to target substances using machine learning algorithms, such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), or Artificial Neural Networks (ANN).

In terms of working principle, the electronic nose detects changes in electrical signals as the sensor array interacts with the target gases. The response patterns correspond to the physicochemical characteristics of the gas components. When a gas mixture passes through the detection chamber, selective interactions—such as charge transfer, mass adsorption, or conductivity changes—occur between the sensitive materials of the sensors and the gas molecules, generating dynamic response curves. A classification model is then trained using a database of known samples to enable qualitative or quantitative analysis of unknown samples. Compared to traditional gas chromatography-mass spectrometry (GC-MS), electronic noses offer advantages such as non-invasive detection, real-time response, and portability. As a result, they have been widely applied in food quality control, environmental monitoring, medical diagnostics, and industrial process control.

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2.2. Diverse applications of the electronic nose in wine detection

Vasiliki Summerson et al. [2] studied the aroma of Cabernet Sauvignon wines contaminated by smoke. They collected aroma data using an electronic nose and performed GC-MS to analyze the peak areas of volatile aromatic compounds. Two different regression models were used to predict the e-nose data, validating the accuracy of the models and revealing the relationship between smoke exposure and specific volatile compounds. This approach offers a rapid and accurate method for assessing the degree of smoke contamination. Margherita Modesti et al. [3] conducted a comparative study on rosé sparkling wines produced using the traditional method and the Charmat method. They collected aroma data using an electronic nose and analyzed the samples using a Partial Least Squares-Discriminant Analysis (PLS-DA) model. The results were compared with measurements obtained via GC-FID, demonstrating that the electronic nose can replace GC methods as a faster and more economical tool for distinguishing wine based on production techniques and fermentation time. Stefano Pettinelli et al. [4] evaluated the aromatic maturity of grapes from different regions. They used an electronic nose to detect volatile gases and processed the data using PCA and hierarchical clustering. Principal Component Regression (PCR) was used to assess the e-nose's ability to predict VOCs. Results showed high predictive power, particularly for aldehydes and benzenes, validating the feasibility of using e-noses for non-destructive quality assessment at the raw material stage in wine production. Sergio Luiz Stevan Jr. et al. [5] examined the ability of an electronic nose to distinguish wines made from different raw materials. They collected VOC data from four types of wines and applied six classification algorithms to categorize the data. Cross-validation was used to prevent overfitting. All classification algorithms achieved accuracy rates above 99% on the test sets, confirming that the electronic nose can effectively differentiate wines based on the volatile characteristics of their raw materials, making it a viable tool for wine quality evaluation. Zhu Hongzhen et al. [6] employed a Latent Dirichlet Allocation (LDA) model for wine detection. They combined molecular formulas and odor names from wines into a set of synthetic "words" to generate topics. A probabilistic multinomial distribution was produced for topics linking odors and chemical molecules. Using the Apriori algorithm, association rules were extracted from frequent itemsets to identify strong correlations between odors and chemical compounds. Jensen-Shannon divergence was used to measure the differences in odor molecule distributions, and hierarchical clustering verified the clustering performance of the LDA model. This confirmed the feasibility of applying LDA models in wine quality assessment.

3. Application of deep learning in wine detection

3.1. Introduction to deep learning methods and principles

Deep learning is a subfield of machine learning that focuses on learning hierarchical data representations through artificial neural networks composed of multiple processing layers—hence the term "deep" learning. A typical deep learning system comprises several key components: an artificial neural network (ANN), activation functions, a loss function, and an optimizer. The ANN consists of numerous interconnected simple processing units (neurons), which are organized into layers. Neurons in adjacent layers are connected via weighted links, through which information is transmitted. Activation functions introduce non-linear transformations, enabling neural networks to capture complex patterns beyond what linear models can represent. The loss function quantifies the error between the predicted output and the actual target, serving as a performance metric. The optimizer adjusts the network weights based on the loss value to minimize the error. In practice, deep learning systems often involve data preprocessing steps such as normalization, standardization, and data augmentation, followed by feature extraction, classification, and dimensionality reduction. When combined with electronic nose data, deep learning can generate gas recognition network models that are better suited to specific datasets. The key advantages of using deep learning include automated feature extraction (which reduces human error), streamlined workflows, improved generalizability, and high tolerance to noise and sensor drift.

3.2. Application of deep learning in electronic nose odor detection

Wang Qian et al. [7] used electronic nose sensors to collect gas data and then applied the SGF-GAF-CNN method for gas recognition. First, a Convolutional Neural Network (CNN) was used to automatically learn deep features from the gas sensor data. Next, multiple filtering techniques—including the Savitzky-Golay filter—were used for data preprocessing. The Gramian Angular Field (GAF) method was then employed to convert one-dimensional time series data into two-dimensional sensor images. To enhance model generalizability and robustness, various data augmentation strategies were adopted. Finally, a fine-tuned GoogLeNet network was used in the pattern recognition stage to classify and identify the combined sensor images. Using this method, the maximum gas recognition accuracy on the dataset reached 99.9%. Furthermore, the SGF-GAF-CNN method was applied to three additional datasets: a public binary gas mixture dataset, a lab-generated ternary gas mixture dataset, and a self-collected ethanol dataset with varying humidity levels. The highest recognition accuracies achieved were 98.5%, 90.5%, and 97.9%, respectively. These results strongly validate the effectiveness of the SGF-GAF-CNN gas recognition approach.

4. Conclusion

This paper analyzed the principles of the electronic nose and deep learning methods and reviewed several application cases of electronic noses in wine detection. The electronic nose offers advantages such as ease of operation, non-contact measurement, no contamination, and non-destructive, objective, and accurate detection. However, it still faces challenges such as low early-stage recognition rates, sensor drift, and dependence on manually extracted features. Deep learning methods, in contrast, provide advantages like automatic feature extraction (reducing human bias), improved generalizability, and higher robustness to noise and sensor drift. When combined with electronic nose systems, deep learning can significantly improve the efficiency and accuracy of gas recognition. Such integrated systems have already been applied in industrial settings and hold great potential for further development, particularly in the field of wine quality assessment.

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