Proceedings of the 3rd International Conference on Mechatronics and Smart Systems
DOI: 10.54254/2755-2721/2025.22546

# *Freshness Detection of Bass Based on Electronic Nose Technology*

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***Abstract:*** As a common aquatic product, the freshness of bass directly impacts food safety and consumer experience. Traditional detection methods are limited by strong subjectivity and high destructiveness, making it difficult to meet the rapid and non-destructive testing requirements of modern food industry. Electronic nose technology provides an efficient solution for bass freshness detection by capturing characteristic volatile organic compounds produced during spoilage. This study systematically reviews the core aspects of this technology: in sample preparation, it standardizes the processing of fish meat and odor collection procedures; in system construction, it introduces the specific response mechanisms of gas sensor arrays to spoilage markers; in data analysis, it compares the application differences between traditional pattern recognition methods and deep learning algorithms. The study also identifies current industrial bottlenecks and future development directions. This study provides technical references for freshness detection in the bass and other aquatic industries, while also exploring technological innovations in the field of food freshness detection.

***Keywords:*** Bass Freshness Detection, Electronic Nose Technology, Volatile Organic Compounds, Pattern Recognition, Deep Learni

## 1. Introduction

As a high-protein, low-fat premium aquatic resource prized for its tender texture and rich nutritional value, bass has become a staple on consumer dining tables. However, its inherent physiological characteristics result in a short shelf life, making it highly susceptible to quality deterioration during storage, transportation, and sales due to microbial proliferation, enzymatic reactions, and lipid oxidation. This degradation manifests not only in softened flesh texture and flavor loss but also in the production of volatile odorous substances such as ammonia, hydrogen sulfide, and trimethylamine, directly impacting consumer experience[1]. More critically, pathogenic bacteria like Pseudomonas and Enterobacteriaceae proliferating during spoilage may cause foodborne illnesses, posing public health risks. Consequently, developing an efficient and accurate freshness detection method has become crucial for ensuring bass quality safety, optimizing supply chain management, and meeting consumer demands [2].

Current freshness detection of fish primarily relies on three conventional methods: sensory evaluation, chemical analysis, and microbial testing. However, these techniques increasingly reveal limitations in modern applications. Although sensory evaluation can intuitively reflect quality changes, its strong subjectivity and lack of quantitative standards hinder large-scale implementation.

Chemical analysis offers high precision but requires complex sample pretreatment processes, consuming several hours and predominantly involving destructive testing [3]. Microbial testing accurately characterizes spoilage levels but demands prolonged detection cycles of 24-48 hours with cumbersome operations, failing to meet real-time monitoring needs [4]. Notably, these methods commonly suffer from high equipment costs and technical barriers, making them inadequate to address the food industry's urgent demand for rapid, non-destructive, and automated detection [5].

Addressing the shortcomings of conventional methods, electronic nose (e-nose) technology has gained significant attention in food quality detection as a novel approach mimicking biological olfaction [6]. This technology employs integrated gas sensor arrays to capture volatile organic compounds (VOCs), combined with pattern recognition algorithms to construct dynamic response profiles [7], forming a complete detection chain from data acquisition to intelligent analysis. Compared with traditional methods, e-nose technology demonstrates three breakthrough advantages [2]: detection cycles can be reduced to minutes, meeting stringent timeliness requirements in industrial production lines; non-destructive gas sampling preserves sample integrity for re-examination; standardized procedures and automated analysis significantly reduce human errors, with detection repeatability improving by 30%-40% compared to manual assessments. These characteristics endow it with unique potential in quality monitoring of fresh food supply chains [8], particularly showing promising application prospects in real-time cold chain logistics monitoring [9].

Still, in the field of bass freshness detection, the use of e-nose technology in practice is a requirement of methodical investigation in three main ways. First, in order to prepare the sample, standardised procedures for the processing of fish meat and the collection of odors, and to deal with the problems of volatile compound stability and microbial heterogeneity in different storage settings, are necessary [3,4]. Second, sensor array design and signal processing mechanisms need optimization to enhance selective responses to bass-specific spoilage markers (e.g., trimethylamine), leveraging advancements in MOS-based sensing materials [5] and dynamic response profiling algorithms [6]. Third, comparative analysis of pattern recognition methods—from traditional PCA/SVM frameworks to deep learning architectures like 1D-CNN-BiLSTM [7,10]—must reconcile algorithmic interpretability with industrial scalability. This study organizes its investigation as follows: Section 2 establishes standardized methodologies for sample preparation and e-nose system configuration; Section 3 evaluates traditional versus deep learning approaches in data analysis; and Section 4 proposes future directions integrating multi-source data fusion [11,9] to bridge laboratory research with industrial deployment. By structuring research across these pillars, this work aims to advance e-nose technology toward robust, field-deployable solutions for aquatic product quality control [1,8].

## 2. Materials and principles

Sample preparation constitutes a critical component in e-nose experiments, where its standardization level directly impacts the reliability and reproducibility of detection outcomes. As a general review paper, this section will systematically elaborate on the general methodology of e-nose technology in fish freshness detection from three aspects: sample handling principles, e-nose system configuration, and operational workflow.

### 2.1. Sample preparation methods

Sample preparation comprises two components: fish meat processing and odor collection, following standardized procedures as outlined below:

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#### 2.1.1. Fish meat processing protocol

**Sample Selection:** Typically, live or freshly caught fish (e.g., bass, salmon) are selected to ensure consistent initial freshness.

**Pretreatment:** Rinse the fish with clean water to remove scales and internal organs, avoiding contamination. Cut the fish meat into uniform blocks (e.g., 2 cm × 2 cm × 1 cm) to ensure sample homogeneity.

**Storage Conditions:** Place processed samples in sterile containers under varying temperature conditions (e.g., 4°C refrigeration, 25°C ambient temperature) to simulate real-world storage environments.

**Sampling Time Points:** Collect samples at specific intervals (e.g., 0 h, 12 h, 24 h, 48 h) to observe dynamic freshness changes over time.

#### 2.1.2. Odor collection protocol

**Sampling Environment:** Conduct odor collection in a sealed, contamination-free, and temperature-controlled environment to minimize external interference.

**Sampling Preparation:** Place fish samples in clean sampling vials, reserving sufficient headspace for gas accumulation.

**Gas Collection:** Allow vials to equilibrate at 25°C for 10 minutes to ensure full volatile release. Insert the e-nose probe to collect headspace gases, typically for 2 minutes.

**Probe Cleaning:** Clean the probe immediately after collection to prevent residual odor interference in subsequent experiments.

### 2.2. E-nose system configuration and working principles

The e-nose is an intelligent sensing device mimicking biological olfaction, widely applied in food freshness detection. Its core modules include a sensor array, gas delivery system, and signal processing unit.

#### 2.2.1. Sensor types and response mechanisms

The e-nose employs a multi-sensor array design, typically comprising about 10 metal oxide semiconductor (MOS) sensors. Each sensor exhibits specific responses to distinct categories of volatile organic compounds (VOCs), operating through the following mechanisms:

**Gas Adsorption:** VOC molecules interact with the sensor's surface-sensitive material, triggering chemical reactions.

**Electrical Signal Conversion:** Resistance changes caused by chemical reactions are converted into electrical signals.

**Signal Transmission:** Preprocessed signals (e.g., baseline correction, noise reduction) are transmitted to the data analysis module.

#### 2.2.2. Sensor application characteristics

In fish freshness detection, e-nose sensors specifically respond to characteristic gases produced during spoilage (e.g., ammonia, hydrogen sulfide, trimethylamine). By analyzing response patterns of the sensor array, quantitative freshness evaluation and classification can be achieved.

#### 2.2.3. Signal processing and data analysis

Post-signal acquisition, the e-nose system processes data through the following steps:

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**Preprocessing:** Apply baseline correction, denoising, and normalization to raw signals to enhance data accuracy and comparability.

**Pattern Recognition:** Utilize algorithms such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), or Support Vector Machines (SVM) for dimensionality reduction and classification, generating quantitative freshness assessment results.

Theoretically guiding the use of e-nose technology as a means of measuring the number of fish that are fresh is provided by the systematic description of the generic approaches that is described in this section; however, the process of establishing the basis for technical developments and advances in related research fields is also being done.

## 3. Data analysis methods

In e-nose-based fish freshness detection, raw data generated by sensor arrays require processing and analysis through pattern recognition methods to extract meaningful information and achieve classification. This paper systematically reviews their applications in bass freshness detection from two perspectives: traditional pattern recognition methods and emerging deep learning approaches.

### 3.1. Traditional pattern recognition methods

In the data analysis workflow of e-nose systems, traditional pattern recognition methods provide foundational technical support for bass freshness detection through multi-dimensional feature extraction and modeling strategies. Principal Component Analysis , as a classical unsupervised dimensionality reduction method, extracts principal components from sensor response data via orthogonal transformation, effectively enabling high-dimensional data visualization and noise filtering. However, its linear transformation characteristics limit the representation of nonlinear interactions among volatile gases during bass spoilage. To address this, Partial Least Squares (PLS) Regression demonstrates higher applicability in quantitative prediction of bass storage time by establishing latent variable correlation models between sensor responses and biochemical indicators (e.g., TVB-N values, total viable counts). Linear Discriminant Analysis (LDA) constructs discriminant feature spaces for freshness level classification by maximizing inter-class dispersion through projection strategies, yet its classification performance is constrained by data normality assumptions and weak adaptability to nonlinear sensor responses.

At the classification algorithm level, SVM leverage kernel function mapping to transform nonlinear data into high-dimensional separable spaces, showing strong advantages in handling complex response patterns caused by sensor cross-sensitivity. For instance, radial basis function kernels effectively capture synergistic variations in amine and sulfide concentrations during bass spoilage. The K-Nearest Neighbors algorithm implements classification based on sample spatial distance metrics, offering rapid deployment advantages in small-scale datasets, but its sensitivity to sensor drift noise may lead to ambiguous classification boundaries. Probabilistic models such as Naïve Bayes classifiers construct posterior probability models under feature independence assumptions, providing computational efficiency suitable for real-time e-nose detection. However, their neglect of sensor response correlations may weaken early spoilage recognition capabilities.

To enhance model robustness, ensemble learning methods optimize system performance through collaborative decision-making by multiple base models. Random Forest algorithms mitigate single-sensor failure risks using multi-decision-tree voting mechanisms, while their built-in feature importance evaluation assists in identifying key sensor units sensitive to bass spoilage. Artificial Neural Networks (ANN) simulate complex relationships between sensor responses and freshness indicators via multi-layer nonlinear mapping, though overfitting risks require attention—regularization strategies can constrain model complexity, particularly with limited samples. Time-

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series feature extraction methods like Discrete Wavelet Transform decompose temporal features (e.g., slopes, peaks, decay rates) from dynamic sensor response curves, providing supplementary information reflecting spoilage progression. Current research trends focus on hybrid model construction, such as feeding PCA-reduced features into SVM classifiers or using PLS-extracted latent variables as ANN inputs. These fusion strategies balance computational efficiency and classification accuracy, offering optimized solutions for the engineering applications of e-nose systems.

### 3.2. Development and advantages of deep learning methods

The introduction of deep learning methods is driving systematic paradigm shifts in e-nose data analysis. Targeting the time-series signal characteristics generated by e-nose sensors, one-dimensional convolutional neural networks (1D-CNNs) enable automatic extraction of local response features through direct sliding mechanisms of temporal convolution kernels. This approach avoids dimensional distortion caused by two-dimensional reconstruction. Its core advantage lies in autonomously uncovering latent pattern features in data through multi-level nonlinear transformations, particularly suitable for gas detection scenarios with fixed response cycles.

Scholars are becoming more aware that temporal dependency modeling is becoming a bigger topic of study because to the increasing number of studies that study complicated spoiling processes. By including gating mechanisms and using them in place of temporal evolution patterns of volatile compound concentrations, recurrent neural networks and their variants are able to effectively record these patterns. An example of Bidirectional Long Short-Term Memory Network (Bi-LSTM) uses dynamic updates of memory units to give systems the capacity to recognize important inflection points in response curves. For the purpose of monitoring the production cycles of distinctive metabolites during the spoiling of aquatic products, this capability is very helpful.

Recent advancements in multi-sensor synergy analysis have spurred interactive modeling methods. By abstracting individual sensors as dynamic nodes in graph structures, graph convolutional networks (GCNs) establish spatial correlation models based on cross-sensitivity parameters. The fundamental breakthrough of these methods lies in revealing systemic response patterns undetectable through single-sensor analyses. However, the interpretability limitations of current deep learning approaches remain unresolved. Balancing data-driven feature discovery with physicochemical mechanism constraints has become a key challenge for enhancing algorithmic reliability.

Traditional pattern recognition methods (PCA, LDA, SVM) have seen long-term applications in bass freshness detection due to their computational efficiency and mechanistic interpretability. Yet their linear assumptions struggle to adapt to the nonlinear response characteristics of sensor arrays toward complex VOCs. Deep learning approaches like 1D-CNNs overcome the limitations of manual dimensionality reduction in traditional methods by extracting time-varying sensitive features directly from raw signals through temporal convolution and hierarchical nonlinear transformations. Compared to the segmented regression strategies for TVB-N thresholds in shallow models, deep learning achieves end-to-end continuous modeling of biomarker concentrations during spoilage, significantly improving weak signal discrimination capabilities. While current applications still require balancing computational costs with model generalization performance, lightweight architectures incorporating physical constraints are emerging as promising solutions to overcome these bottlenecks.

## 4. Conclusion

This study gives a fuller technical study of bass newness detection by means of the method of systematic analysis of classic and deep learning methods of pattern recognition method. Traditional

DOI: 10.54254/2755-2721/2025.22546

method shows great performances in basic situation, whereas the deep learning method is more applicable to complicated situation. The deep learning technology in the future can also combine the traditional method with deep learning technology, so it can improve the accuracy and the efficiency of bass newness detection more effectively and efficiently.

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