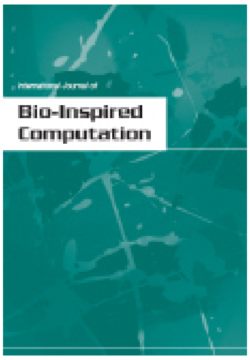

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Classification techniques of electronic nose: a review

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Abstract: Electronic nose (e-nose) is composed of a set of gas sensors combined with a series of algorithmic models. The practical application of the electronic nose system can prove that the electronic nose is more widely used in the classification problems, and always has a good performance. Moreover, it can be inferred that classification methods significantly influence e-nose. So far, the classification models proposed in e-nose can generally be divided into two categories. One is the linear classifier, representing the model of the Bayesian classifier, principal component analysis (PCA), and K-nearest neighbour (KNN), etc. The other is the nonlinear classifier, including support vector machine (SVM), random forest (RF), and extreme learning machine (ELM), etc. This review aims to supply a summary of the various classification methods used in e-nose, and provides a reference for the choice of an appropriate classification model used in e-nose in the specific application.

Keywords: electronic nose; e-nose; classification techniques; artificial intelligence algorithm.

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1 Introduction

As a device that mimics the mammalian olfactory organ, the electronic nose (e-nose) includes an array of sensors to sense special gases and an appropriate pattern recognition classification system. It is effective in dealing with odour analysis problems (Głowacz et al., 2021; Lu et al., 2014; Moufid et al., 2021; Chen et al., 2013), and during the past decades, the e-nose technology has been introduced to many fields such as quality control of food industry (Konduru et al., 2015; Dai et al., 2015; Längkvist et al., 2013; Wen et al., 2021; Hartyani et al., 2013; Pan et al., 2014; Wijaya et al., 2021), environment protection (Romain and Nicolas, 2010; Jiang et al., 2017; Zhang et al., 2020; Wang et al., 2018; Wilson, 2012), public health (Adiguzel and Kulah, 2015; Lee et al., 2022; Bruins et al., 2013; Burfeind et al., 2014; Luo et al., 2018), explosives detection (Brudzewski et al., 2012; Norman et al., 2003) and spaceflight applications (Young et al., 2003).

Main hardware composition of e-nose is the sensor array system composed of electronic chemical sensors, metal oxide sensors or other types of sensors. At the same time, the e-nose also has the software part that can extract the feature information and the pattern recognition classification algorithm. In order to accurately extract the useful information and classify it, the system needs to use the algorithm model to find the desired part from the response data of the sensor and conduct the corresponding data processing.

Analysing the structural composition of the e-nose, the system can improve the overall performance from three aspects: replacing the sensor materials, optimising the sensor array, and improving the feature extraction and pattern recognition algorithm model. In general, most of the papers aimed to improve the performance of e-nose are, focusing on optimising the three types.

Although e-nose is used to carry out qualitative classification analysis and quantitative regression analysis, extensive experiments have proved that the application of e-nose in the classification problem is more widely and always shows excellent performance. Some traditional classification methods in many fields have brought great inconvenience. In addition, some poor classification technology can not classify things successfully but also may even cause damage to the nature of the object itself. Thus, a piece of classification equipment with a high recognition rate like e-nose will have a significant meaning in many fields. Similarly, for an e-nose, a kind of appropriate classification method plays a crucial role in improving its performance. So the study of classification algorithms on e-nose becomes crucial.

The classification algorithm aims mainly to distinguish between the things that are not easy to distinguish direct and ensure a high recognition rate for a specific application. For most of the classification methods, its classification process can be depicted as follows:

Firstly, the dataset is proportional divided into training data and test data, and the classifier is trained with the help of training data.

Then, the absolute accuracy of the classifier is then used as a key evaluation indicator of the system to evaluate the performance of the e-nose.

A classification algorithm is difficult to be the best method for all e-nose systems, and it needs to be found based on factors like detecting the gas target, the sensors used, and the field conditions applied. Based on this background, we have several motivations to perform this study as follows:

1 This paper summarises the excellent classification methods used in recent years.

2 By comparing and introducing different e-nose classification algorithms, the advantages and disadvantages of various classification algorithms can be intuitively understood.

3 This paper can be inferred that classification methods significantly influence e-nose.

Then the linear classification methods are summarised and described clearly in Section 2. Some familiar ANN algorithms applied to the classification problem in e-nose are involved in Section 3. An overview of the SVM algorithm and some specific applications are discussed in Section 4. Finally, the conclusions are drawn in Section 5.

2 Linear classification methods

This section mainly details several representative linear methods, including principle component analysis (PCA), discriminant analysis, partial least squares regression (PLSR), K-nearest neighbour (KNN), and Bayes classifier.

2.1 Principle component analysis

PCA, a linear and unsupervised classification method, is a multivariate technique that analyses a data table in which several inter-correlated quantitative dependent variables describe the observations (Abdi and Williams, 2014).

As a classical classification and recognition method, PCA has been widely applied to the classification of e-nose. For instance, Capone et al. selected a dynamic PCA analysis to process the data and follow the evolution of the data clusters related to different ageing days. Their studies indicated that dynamic PCA analysis allowed us to obtain a correlation between rancidity and ageing days of milk (Capone et al., 2001).

Hu used an e-nose to detect crop peat information, and the PCA was applied to do the recognition analysis for the measured data each time based on 'non-pest' (OBPH) and 'pest group' (5 BPHs–10 BPHs). The result indicated that the number of pests on each rice stem could be easily classified via PCA and e-nose was able to detect crop pest information (Hu, 2006).

Tian et al. designed an e-nose system consisting of a MOS gas sensor array, which showed excellent performance in detecting the freshness of hairtail and pork at different storage temperatures (15°C, 10°C, and 5°C). The results showed that the sensor array coupled with PCA could be trained to distinguish between the fresh and rotten samples in real-time and identify the storage days by testing the change in volatile components (Tian et al., 2012a).

Some researchers attempted to achieve the classification and recognition of rough rice via regular PCA based on e-nose, but it did not reach an ideal situation (Zheng et al., 2009; Hu et al., 2011). So Xu et al. (2014) proposed a method that combines PCA with the Wilks-statistic, which is typically used to test or examine the differences between two or more populations to recognise six varieties of rough rice (Zhongxiang1, Xiangwan13, Yaopingxiang, Wufengyou T025, Pin36, and Youyou122) based on a PEN3 e-nose (Xu et al., 2014). The results showed that the Wilks-statistic could effectively improve the classification accuracy of regular PCA (Ji et al., 2021).

Of course, regardless of whether the performance of PCA is good or not, because of the space constraints many applications (Dymerski et al., 2014; Yin and Tian, 2007) based on PCA have not been mentioned in the paper. Although PCA can classify something, it is more applied in the data processing.

2.2 Discriminant analysis

In the application of e-nose, the most common discriminant analysis method is the LDA (Lerma-García et al., 2010; Yin et al., 2017; Gómez et al., 2006a, 2006b; Mahmodi et al., 2019; Siqueira et al., 2017; Xiong et al., 2014), also called Fisher's linear discriminant (FLD).

As a classical classification and recognition method, LDA has been widely applied to the classification of e-nose. For instance, LDA was applied to the patterns generated to classify edible vegetable oils by chemometric treatment of the data obtained from an array of gas sensors (Lerma-García et al., 2010). Nevertheless, due to its linear characteristic, the classification problems of multi-class and high-dimensional e-nose data cannot be handled effectively. Therefore, a Gaussian-based kernel FDA (KFDA) method was proposed to solve complex samples' multi-class and high dimensional classification problems such as food classification (Yin et al., 2017). Furthermore, LDA was usually used to compare with other classifiers like PCA, QDA, CDA, etc.

For example, in identifying the maturation problem of tomato and citrus, many studies (Gómez et al., 2006a, 2006b) have shown that LDA performs better than PCA. That's to say, the linear discrimination method of LDA is more well suited to solve such problems.

Besides LDA, another two discriminant analysis methods (QDA, CDA) also have appeared in the application of e-nose, but they are not the same common as LDA. The only difference is that the LDA should be used when the covariance matrix of the different classification samples is the same, otherwise the classification will choose the QDA (Mahmodi et al., 2019; Siqueira et al., 2017).

CDA, a supervised classification approach that can solve the classification problems of more than two classes, was used to discriminate the freshness of juices on Hong and Wang (2015).

Because of the linear character of DA methods, they can perform well in linear problems. When solving multi-class and high dimensional classification problems, there is usually some improvement like adding kernel functions based on them. Most of the time, LDA is used as a comparison algorithm of other classification methods.

2.3 Partial least squares regression

PLSR, a novel multivariate statistical analysis method, mainly studies the regression modelling of the multiple dependent and independent variables. In contrast to the PCA with only one independent variable matrix, a 'response' matrix is included in the PLSR method besides. So PLSR has a good prediction capacity (Zhang et al., 2012).

PLSR was also used to apply e-nose as a classifier but with few times. In Gudrun et al. (2005), PLSR based on samples from single producer showed an excellent performance in classifying the quality of different cold-smoked salmon samples. Because PLSR is not widely applied in the e-nose, we only do a simple introduction about it.

2.4 K-nearest neighbour

KNN also appeared in the application of e-nose as a classification method for a long time. In pattern recognition, the KNN algorithm is a non-parametric method used for classification and regression (Güney and Atasoy, 2012). Tang et al. (2010a) developed a prototype of a portable e-nose embedded with a KNN algorithm for odour classification to identify the fragrance of three fruits, namely lemon, banana, and litchi. In Shao et al. (2015), KNN and other classifications were applied to characterise sesame oils processed by three different methods (hot-pressed, cold-pressed, and refined) based on an e-nose (Alpha MOS, Toulouse, France). The experimental data showed that the KNN predictions are best at k values of 1 and 2. A new e-nose instrument was used for the detection of colorectal cancer (CRC) by the success of re-classification using an $(n - 1)$ KNN algorithm showing 78% sensitivity and 79% specificity to CRC (Westenbrink et al., 2015). In some cases, the standard KNN method cannot reach an ideal effect since several improved KNN algorithms have been proposed for specific applications of e-nose. For instance, the proposed KNN method with decision tree structure was used to classify different n-butanol concentrations using e-nose (Güney and Atasoy, 2012). The components of an odour were determined by an e-nose with a KNN-based local weighted nearest neighbour (LWNN) algorithm (Tang et al., 2010b). Besides KNN, the local KNN and discriminant adaptive nearest neighbour (DANN) were also employed in e-nose (Bicego et al., 2002).

2.5 Bayes classifier

In statistical classification, the Bayes classifier is best characterised by minimising the misclassification probability. Suppose a pair (X, Y) takes values in $R^d \times \{1, 2, \dots, K\}$, where Y is the class label of X. This means that the conditional distribution of X, given that the label Y takes the value r is given by

$$X|Y = \tau \sim P_\tau \text{ for } \tau = 1, 2, \dots, K \tag{1}$$

where denotes a probability distribution.

In theoretical terms, a classifier is a measurable function C: $R^d \rightarrow \{1, 2, \dots, K\}$ with the interpretation that C classifies the point x to the class $C(x)$. The probability of misclassification or risk of a classifier C defined as

$$\Re(C) = P\{C(X) \neq Y\} \tag{2}$$

The Bayes classifier is

$$C^{Bayes}(x) = \arg\max\ P(Y = \tau | X = x)\ \tau \in \{1, 2, \dots, K\} \tag{3}$$

In practice, as in most statistics, the difficulties and subtleties are associated with modelling the probability distributions effectively – in this case $P\{Y = \tau|X = x\}$. The Bayes classifier is a valuable benchmark in statistical classification.

The excess risk of a general classifier C (possibly depending on some training data) is defined as $\Re(C) - \Re(C^{Bayes})$. Therefore, this non-negative quantity should also be used as an evaluation indicator when evaluating the model performance of various classification algorithms. The classifier is consistent on the basis that the number of data in the training set tends to infinity when the corresponding excess risk value converges to zero.

E-nose systems, like human olfactory organs, can classify them by the smell of food samples. Considering this issue, researchers proposed a multi-sensor data fusion based on the Bayesian theorem, which is applied to the data obtained from e-nose and e-tongue for classification and quality assessment of black tea (Banerjee et al., 2014; 2011). Besides, Robust Bayesian Inference also has been explored to classify eight kinds of gases (C_3H_8, C_6H_6, CH_2O, CL_2, CO, CO_2, NO_2, and SO_2) based on e-nose by using random matrix theory (Hassan and Bermak, 2015).

Bayesian classification strictly within the category of statistical classification. Linear classifiers are mainly classified based on the linear combination of information of features. Such a classifier works well for practical problems such as document classification. It is more generally applicable to problems with many variables (features), reaching accuracy levels comparable to nonlinear classifiers while taking less time to train and use (Yuan et al., 2012). What's more, the calculations of the linear classifier are so simple that they can sprint on the single-chip microcomputer and cost fewer resources. But recognition rate will be the focus of attention when the classification algorithm runs on computer and there are enough resources.

Both PCA and PLSR belong to the representative dimension reduction algorithms. KNN is more like a model built based on the instance, and still has a strong dependence on the original data sample instance. Bayesian algorithms, refers to the implicit use of Bayesian principles in classification and regression problems.

3 Artificial neural networks

Artificial neural networks (ANNs) originates from biological neural network and is a mathematical algorithm model that can conduct distributed parallel information processing. Therefore, it appears frequently in many practical applications of solving information processing. The attractiveness of ANNs comes from their remarkable information processing characteristics pertinent mainly to nonlinearity, high parallelism, fault and noise tolerance, and learning and generalisation capabilities (Casey et al., 2019).

Numerous research literature can show that neural network models also perform well in the problem of e-nose classification. This section mainly introduces several neural network models performing well in classification, RBFNN, BPNN and ELM.

In recent years, the first-level application research of ANN includes knowledge engineering, robot control, pattern recognition, optimisation combination and signal processing, etc. With the further development of neural network theory and technology, the application of neural network will be more popular. Of course, deciding which network works better for a given problem depends strictly on the problem logistics. The experimenters can't simply judge which kind of neural network structure is the best.

3.1 Radial basis function networks

Radial basis function (RBF) networks, first formulated in a paper written by Broomhead and Lowe, are ANNs that use RBFs as activation functions (Broomhead and Lowe, 1998a, 1988b). The network works by using a linear combination of the RBF and the neuronal parameters. This working principle supports it for system control, time series prediction and classification, etc.

The basic structure of the RBF network usually includes the input layer, the hidden layer (the nonlinear RBF activation function), and the output layer. The real number vectors $x \in R^n$ are used as the input values. The scalar function corresponding to the real number vector of the input is the output form of the algorithmic model $\varphi: R^n \rightarrow R$ and is given by

$$\varphi(x)=\sum_{i=1}^{N}\alpha_i \rho\left(\|x-c_i\|\right) \tag{4}$$

where the number of neurons with the formula located in the hidden layer is N, the centre vector of the neuron i is c_i, and the weight of neuron i for linear output neurons is expressed as α_i. Since the value of the real-valued function is only related to the distance from the origin, the function is defined as a RBF. The general composition of the network is that the inputs are all connected with the hidden neurons. The norm in equation (5) generally takes the value as the Euclidean distance and the Gaussian function form is chosen to represent the RBF. Equation (5) is as follows:

$$\rho\left(\|x-c_i\|\right)=\exp\left[-\beta\|x-c_i\|^2\right] \tag{5}$$

The Gaussian RBF has only local significance for the central vector.

$$\lim_{\|x\|\rightarrow\infty}\rho\left(\|x-c_i\|\right)=0 \tag{6}$$

That's to say, the distance size of the central neurons from the other neurons is largely independent of the neuronal parameters. When certain mild conditions are satisfied, R^n is defined as the universal approximators RBF of a compact subset. The RBF network with a hidden layer can fix the parameters α_i, c_i and β_i by optimising the fit between φ and the data.

In recent decades, RBF networks (Evans et al., 2000; Dutta et al., 2004) have been widely applied to the classification of e-nose. For example, commercial wheat samples were successfully evaluated using RBF network as classifier in Evans et al. (2000). Yin et al. (2008) proposed a feature extraction method based on wavelet packet analysis with RBF network to discriminate three kinds of Chinese vinegar. The RBF network was performed to differentiate *L. japonica* samples stored for different months by using e-nose in Xiong et al. (2014).

New electric quartz (PZQ) sensing material was designed, and used the six-bulk acoustic wave polymer-coated technology. In the test experiment, 346 volatile samples were selected, involving three categories of edible oil. The sensor array of this system contained six different sensors. The number of output nodes of the network was consistent with the number of sample types, so the network architecture of the RBF is 6-6-3. Relevant experimental data and results presented in this paper are shown in Table. 1. The data showed that the classification rate of the vegetable oil test samples was above 99%, and only one sunflower oil sample has been wrongly identified as non-virgin olive oil (Ali et al., 2003).

Table 1 RBF 6-6-3 network results

Class	*Non-virgin olive oil*	*Sunflower oil*	*Extra virgin olive oil*	*Total*	*Correct (%)*
Non-virgin olive oil	42	0	0	42	100
Sunflower oil	1	33	0	34	97.06
Extra virgin olive oil	0	0	37	37	100

3.2 Back-propagation network

In the neural network model, it is necessary to continuously adjust a certain weight size to better solve a specific problem. The network model obtained after weight adjustment has real and unique characteristics. For this type of network, the most common learning algorithm is called BP (Men et al., 2007; Brezmes et al., 1997; Srivastava, 2003; Kermani et al., 2005, 1999; Fu et al., 2007).

Even in the absence of data feedback, the BP network can feed the multilayer data into the neural network. These networks are versatile and can be used for data modelling, classification, forecasting, control, data and image compression, and pattern recognition (Casey et al., 2019). A BP network with a hidden layer was used to discriminate five different aromatic species (Brezmes et al., 1997). And some of the volatile organic compounds (VOCs) also have been classified by it (Srivastava, 2003).

3.3 Extreme learning machine

Extreme learning machine (ELM) is an improved algorithmic model based on FNN. ELM was first proposed by Huang et al. (2004) to solve the problem of supervised learning. Later, ELM can also solve the problem of unsupervised learning. Compared with other models, ELM has better performance in learning rate and generalisation ability. Some improved versions of ELM also enable representational learning through deep structure.

Simulation results on manual and practical large-scale applications also demonstrate the excellent performance of the ELM algorithm model. The application of the algorithm has been extended to computer vision, environmental science, and bioinformatics. So far, ELM has been widely used in many applications, such as sales forecasting (Yi et al., 2021), mental tasks (Shi et al., 2021), face recognition (Ma et al., 2022) and food quality trace (Shang et al., 2018).

Qiu et al. (2015) selected various experimental methods of sterilisation, washing and fruit juice preservation, and the detection results of ten metal oxide semiconductor (MOS) sensors are also compared. The purpose of the e-nose system in this paper is to compare the performance of ELM, LVQ and Lib-SVM in classifying strawberry juice. The experiment will take the 15 randomly selected samples from the two datasets as the training set, and the remaining five samples will be tested as the test set. After constant debugging of the ELM model parameters, the number of hidden nodes of the model is finally set to 20. Experimental data in Table 2 can intuitively indicate the selective results of the three models for the detected objects. The results indicate that ELM is a good choice for electronic nasal data to process (Qiu et al., 2015).

Table 2 Comparative classification results of LVQ, Lib-SVM and ELM

Model	*Training rate (%)*	*Testing rate (%)*	*Running time (s)*
LVQ	96	100	354
Lib-SVM	99	100	0.0035
ELM	100	100	0.1886

The correlation study on the degree of ELM classification algorithm affected by parameters can also be seen in some literature, which mainly focuses on the selection of input weights and hidden layer thresholds (Huang et al., 2006). During the bacterial detection of the quantum behavioural particle swarm-optimised (Yan et al., 2016), Peng et al. proposed a novel multi-class classification method based on kernel extreme learning machine (QPSO-KELM). Experiments used the presence of uninfected and infected with *Staphylococcus aureus*, *Escherichia coli*, and *Pseudomonas aeruginosa* to judge the four different wounds. The time and frequency domain features of the sample are used to extract the processing data, and the performance index is obtained by leaving one and leaves method. Apart from KELM, another four classification models (SVM, LDA, KNN, and QDA) are applied for comparison.

All the results of classification are shown in Tables 3–5. No matter which feature extraction method was selected, the KELM showed the best performance compared with other classification methods in Table 3. When QPSO, particle swarm optimisation (PSO) algorithm (Poli et al., 1995), genetic algorithm (GA) (Jiang et al., 2014) and grid search (GS) algorithm are employed to optimise parameters of KELM with wavelet coefficients used as features, we can see that the classification rate of QPSO-KELM model obtains 95% and far more than other algorithms in Table 4. Table 5 implies that the Gaussian kernel is the most appropriate kernel function for EKLM. So the experimental results demonstrate the superiority of QPSO-KELM based on e-nose in bacteria detection (Peng et al., 2016).

Table 3 Classification results of different feature extraction methods (%)

Feature extraction class	*KELM*	*ELM*	*SVM*	*LDA*	*KNN*	*QDA*
Peak value	86.25	76.25	80.00	70.00	80.00	73.75
Integral value	90.00	77.50	82.50	72.50	78.75	78.75
Fourier coefficients	91.25	83.75	87.50	81.25	88.75	83.75
Wavelet coefficients	95.00	85.00	88.75	85.00	86.25	85.00

Table 4 Comparison with different optimisation methods for KELM (%)

Class	*QPSO*	*PSO*	*GA*	*GS*
Total	95.00	88.75	87.50	86.25

Table 5 Classification results of four kernel functions used in the QPSO-KELM model (%)

Kernel functions	*Gaussian*	*Linear*	*Polynomial*	*Wavelet*
Total	95.00	85.00	91.25	92.50

3.4 Other ANNs

Learning vector quantisation (LVQ) is a classification algorithm applying the winner-take-all training algorithm. This classification algorithm usually requires a short convergence time when processing sample datasets compared to other algorithm models. The previous work proved that fuzzy learning vector quantisation (FLVQ), which is LVQ and fuzzy theory, showed high recognition capability to discriminate various single odours, even mixture odour (Jatmiko et al., 2006). But its result could be influenced by selecting the best codebook vector. This problem was solved by adding the PSO method to select the best codebook vector (Jatmiko et al., 2009). Of course, in addition to the above several kinds of ANNs, some other ANNs classifiers also have been applied to e-nose, such as KIII (a chaotic neural network) (Fu et al., 2007), self-organisation mapping networks (SOM) (Men et al., 2007), probabilistic neural network (PNN) (Dutta et al., 2004), the multilayer perceptron (MLP) (Mamat et al., 2011; Pardo and Sberveglieri, 2002).

After research and development, the ANN has made many achievements in solving practical problems.

4 Support vector machines

To solve the complex nonlinear classification problem, the SVM of machine learning is one of the most classical and popular models. The problem of SVM model research is extending from linear separable to linear inseparability.

SVM is one of the most common methods used for classification problems based on e-nose (Distante et al., 2003). It is a machine learning method introduced by Vapnik based on the small sample statistical learning theory (Feng et al., 2022; Li et al., 2021). The SVM algorithm finally solves is the sample maximum-margin hyperplane $y = w \cdot x + b$. The basic idea of computing is to calculate economic risk and to optimise structural risk.

For linearly separable two types of data $\{(x_i, y_i)\}_{i=1}^{n}$, where x_i is the sample of which the label is +1 or –1, d is the dimension value, y_i is the label of x_i, and n is the number of samples in the training dataset.

The formula for separating the hyperplane is shown in equation (7).

$$\begin{aligned} &\min \frac{1}{2}\langle w, w\rangle + C\sum_{i=1}^{n}\xi_i, \\ &\text{s.b.} \langle w, x_i\rangle + b \geq +1-\xi_i, \text{ for } y_i = +1 \\ &\quad \langle w, x_i\rangle + b \leq -1+\xi_i, \text{ for } y_i = -1 \\ &\quad \xi_i \geq 0, \forall i \end{aligned} \tag{7}$$

where ξ_i is called the slack variable, and C is the penalty factor. When dealing with the dual optimisation problem, equation (7) requires Lagrangian multiplier transformation to obtain equation (8):

$$\begin{aligned} &\min \frac{1}{2}\langle w, w\rangle + C\sum_{i=1}^{n}\xi_i, \\ &\text{s.b.} \langle w, x_i\rangle + b \geq +1-\xi_i, \text{ for } y_i = +1 \\ &\quad \langle w, x_i\rangle + b \leq -1+\xi_i, \text{ for } y_i = -1 \\ &\quad \xi_i \geq 0, \forall i \end{aligned} \tag{8}$$

$w = \sum_{i=1}^{n}\alpha_i y_i x_i$ represents the optimal expectation weight vector of the discriminant hyperplane. So the best discriminant hyperplane can be derived as:

$$f(x) = \sum_{i=1}^{n}\alpha_i y_i \langle x_i, x\rangle + b \tag{9}$$

The hyper-plane determined by equation (9) is linear, so it can be directly applied to linear classification problems. For the treatment of nonlinear problem, hyperplane needs nonlinear transformation with the help of mapping function. Assuming that the mapping function is $\psi(x)$ in the high-dimensional feature space, then the data obtained from the dot-product formula will be the only influence parameter of the algorithmic model. Define k is such a kernel function as follow:

$$k(x_{i,j}) = \langle \Phi(x_i), \Phi(x_j)\rangle \tag{10}$$

In equation (10), in terms of a kernel function expressed the dot product in high-dimension space. Similar to the linear hyperplane-solving equation (9), the nonlinear problem also has a corresponding discriminant function:

$$f(x) = \sum_{i=1}^{n}\alpha_i y_i k(x_i, x) + b \tag{11}$$

In general, SVM has four classical kernel functions: Gaussian (Qiu et al., 2015; Chen et al., 2011; Tian et al.., 2012b; Brudzewski et al., 2004, 2006), linear (Brudzewski et al., 2004), polynomial (Brudzewski et al., 2004, 2006) and Sigmoid. The performance of the SVM is significantly affected by the kernel function. The Gaussian function is also the simplest structure and the fastest computational rate among the four classes of kernel functions. Gaussian function is a kernel function based on a RBF. Therefore it is also often called an RBF kernel function. Equation (12) is the specific expression of the Gaussian kernel function.

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{12}$$

When the SVM is selected as the classification algorithm, the Gaussian kernel function becomes the preferred collocation form of the e-nose system among the four kernel functions.

Table 6 Comparison of discrimination results from KNN, ANN and SVM models (%)

Models	*PCs*	*Training set*	*Test set*
KNN	4	95.00	90.00
ANN	4	100.00	87.50
SVM	4	100.00	95.00

In the issue of distinguishing between green tea grades, Chen et al. constructed a gas sensor array with eight MOSs sensors, and compared the classification performance of the KNN, ANN and SVM models (Chen et al., 2011). The number of experimental green tea samples was selected as 100, which was divided into the training set and the test set in a ratio of 6:4. The number of green tea samples for the four grades was also fixed. In the method selection of extracting the feature information of the samples, this paper adopted the principal component analysis method, in which the number of PCs is uniformly set to 4. The different discrimination results brought by the three models are shown in Table 6.

The data in the table showed that there is no difference between the results SVM and ANN of the training set, and overall outperforms the KNN model. However, the results of the test set clearly show that SVM is better than KNN and ANN. According to the theoretical knowledge of the machine learning algorithm can clearly explain the diverse results. The relationship between the data collected by the electronic nasal system and the quality of green tea is more complicated. For complex classification problems, nonlinear algorithm models will be more applicable.

Tian et al. (2012b) used the SVM classifier to analyse the rat wound odour to determine the infection type. Infection is divided into four main conditions: pseudomonas *Aeruginosa*, *Escherichia coli*, *Staphylococcu saureus* or uninfected. To illustrate the advantages of the SVM model, the classification results of BP and RBF are used as comparison. It is necessary to find the penalty and kernel parameters of the kernel function of RBF by GA. GA is also used to optimise the parameters of three classifiers. The maximum response values of normalised sensor are used as features for classification. In the RBF kernel function $K = (x_i, x_j) = \exp(-\gamma\|x_i - x_j\|^2)$, the best values of kernel parameter γ and penalty parameter C were found by the GA.

Table 7 shows the recognition results of the three classifiers and their time consumption with GA method. According to the results, although BPNN can receive the same reasonable classification rate as SVM, the time consumption is much longer than those of the SVM and RBF network. In summary, SVM combined GA is a useful tool for classification the case of small sample. Meanwhile, it can achieve a rapid and accurate detection effect of the wound infection situation.

Table 7 Classification rate and time consumption for three classifiers combined GA-based parameter optimisation

Classifiers	*Classification rate*	*Time consumption*	*Optimal parameters*
SVM	91.25% (73 of 80)	4,427 s	C = 440,070 γ = 0.0675
BPNN	91.25% (73 of 80)	405,180 s	Goal = 0.016*
RBFNN	85% (68 of 80)	82,241 s	σ =5.7362 Goal = 0.0426

Notes: The 104 optimised initial weights and bias are not given here.

In addition to the above mentioned, some improved SVM algorithms are used for different application of e-nose. For instance, the SVM neural network was applied to classify several odours using the e-nose (Brudzewski et al., 2004, 2006). E-nose was used to classify different *n*-butanol concentrations with the proposed SVM method in decision tree structure (Güney and Atasoy, 2012). Some improvements about the SVM method have not been used in the classification problem. We would like to see more research about SVM based on the e-nose classification problems in the future.

But it is sensitive to missing data, and there is no universal solution for nonlinear problems, so we must be careful to choose kernel function to deal with different problems.

5 Conclusions

Nowadays, e-nose systems have limited application of deep learning algorithm models. In the future, more models can be combined with sensor arrays to further improve the system performance. Through the optimisation of the algorithmic model, the e-nose system is expected to solve the more demanding classification problem. The examples of qualitative classification analysis and quantitative regression analysis are common. In many areas where traditional classification methods cannot meet people's production and living needs, e-nose systems are fully competent for the work.

This paper has presented an overview of the various classification methods used in the e-nose in recent years, and illustrates some examples targeted applications. The research problems and experimental results of some application examples can show that the e-nose system has brought help and convenience in the diverse fields. Of course, there will be more efficient classification models besides the classification methods mentioned in this paper.

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