Journal of Computer Science

Review

Survey on Applications of Electronic Nose

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Article history
Received: 01-08-2019
Revised: 22-08-2019
Accepted: 13-03-2020

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Abstract: Food plays a vital role in our daily life. Providing good quality food to consumers is essential. Food quality can be accessed using the Electronic nose. Electronic nose (E-nose) is an instrument for odor analysis. E-nose mimics the human olfaction system. It is widely used in predicting the quality of foodstuffs and detecting the contamination in foods. E-nose can also be used in outdoor monitoring such as air quality monitoring and detect the hazardous odors emitted wastewater treatment plants. Application of E-nose is increasing day by day. In this paper, we consolidated the previous works on E-nose. They had applied different machine learning algorithms to construct a model. In most of the works, for the classification of data, they used Support Vector Machine and Linear Discriminant Analysis, which shows higher accuracy when comparing to other algorithms.

Keywords: Electronic Nose, Food Quality, Support Vector Machine, Linear Discriminant Analysis, Support Vector Regression

Introduction

Traditionally, human tester involved detecting the contamination level of fruits, vegetables, dairy products, animal foods based on the appearance, colour and aroma. It is an inefficient method. E-nose is a non-destructive method to test the quality of products. In 1982, Dodd and Persuade introduced E-nose system. It can detect the volatile compounds emitted from various source. E-nose consists of an array of sensors. Sensors are selected based on applications. E-nose responses are collected using microcontrollers like Arduino, Raspberry pi. PCA (Principal Component Analysis) is one of the feature extraction techniques to choose the important feature in E-nose data. Machine learning algorithms such as Naive Bayes (NB), Support Vector Machine (SVM), Linear Regression (LR), Logistic Regression, Linear Discriminant Analysis (LDA), Support Vector Regression (SVR), Partial Least Square Regression (PLSR), Artificial Neural Networks (ANN) and K-Nearest Neighbour (KNN) are applied to the datasets and performance are analysed.

The electronic nose has a significant impact on outdoor monitoring. Humans can't work in specific odor analysis like detecting the gases emitted from the wastewater treatment plant and detecting toxic gases in the air. But E-nose provides an efficient approach to outdoor monitoring. Electronic nose was used in predicting the ripening stage of fruit and also detect the quality of fruit. Nowadays, Human disease is detected using E-nose from the breath sample (Goor *et al*., 2018). E-nose applications are outlined in the Table 1 and hierarchical chart is shown in Fig. 1. The performances of machine learning algorithms are given in Table 2.

Electronic Nose in Outdoor Monitoring

The electronic nose can be employed in the area where humans can't detect the odor. For example, wastewater treatment plant emits malodorous, which cause serious health issues on humans. Blanco-Rodríguez *et al*. (2018) Suggested a method for characterizing the hazardous gas emitted from the wastewater treatment plant using electronic-nose. In their experiment, odor samples collected from the six stages of the plant. They performed signal filtering, normalization and feature extraction with the dataset. They established the correlation between E-nose response and olfactometry analysis by using Partial Least Square Regression (PLSR).

Nowadays, Air pollution is a significant concern in this world, which has a severe impact on human health. Jasinski *et al*. (2018) suggested a method for predicting the toxic gases present in the air. They used three types of electronic nose system depending upon the type of sensor used semiconductor sensor, amperometric sensor and third one combination of both sensors. They had collected the data in 1 minute from each electronic nose and applied PLS regression and SVM. They compared the performance of all three systems. They measured the concentration of the four gases carbon monoxide (CO), Nitrogen dioxide (NO_2), Sulphur dioxide (SO_2) and ozone (O_3) Among the three types of Electronic nose, a combination of both sensors provides better results.

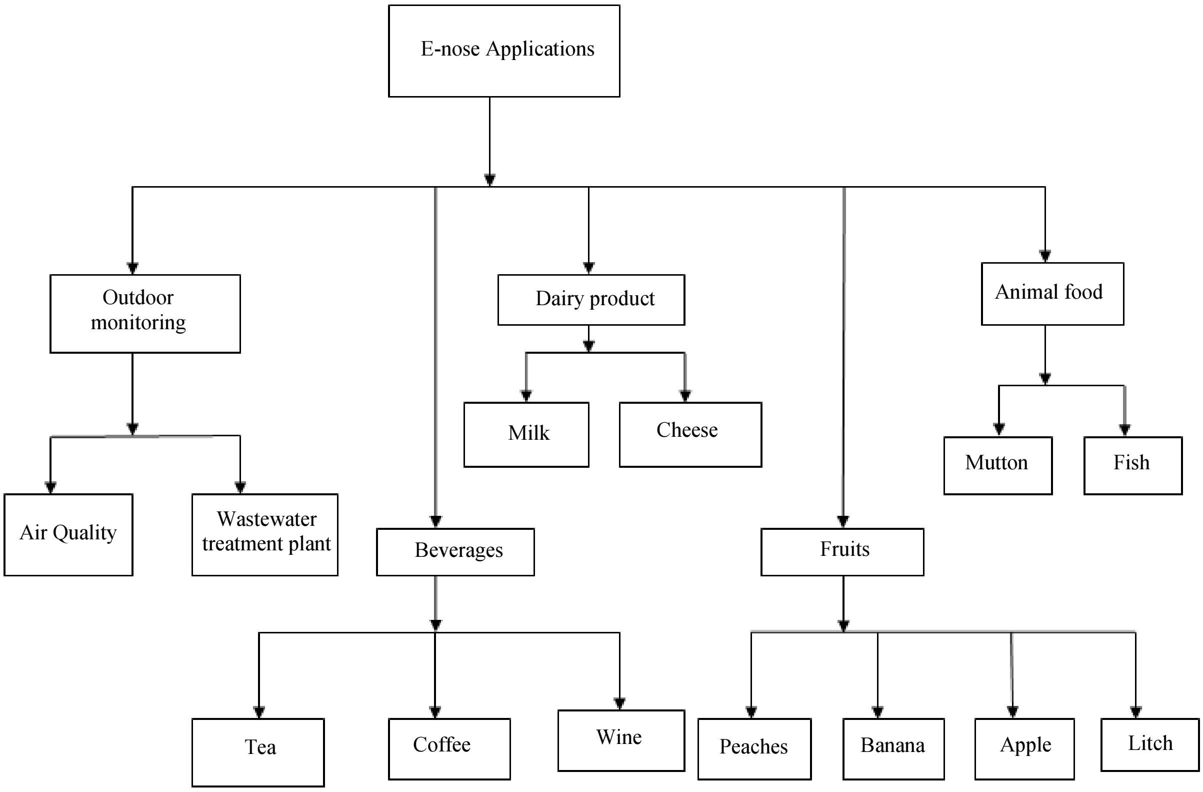

Fig. 1: Hierarchical chart

Table 1: Electronic nose applications

No	Data	Purpose	E-nose configuration	Reference
1	Wastewater treatment plant	Characterize the hazardous gas emitted from the wastewater treatment plant using electronic-nose	TGS2611, TGS2602, TGS2610, TGS826 and TGS2600	(Blanco-Rodríguez *et al*., 2018)
2	Air	Detect toxic gases in the air	Semiconductor sensors and amperometric sensors	(Jasinski *et al*., 2018)
3	Potato	To detect soft rot disease in potato	Warwick OLFaction	(Rutolo *et al*., 2018)
4	Apple	To detect and recognize the fresh and moldy apple	PEN3	(Jia *et al*., 2019).
5	Herbal medicine	To classify the Chinese herbal medicine of 12 types	TGS (Taguchi gas sensors)	(Zhan, 2018)
6	Cherry Tomato	To detect the quality of cherry tomato and classify them into four groups	Ammonia, sulphur compounds, Hydrogen, Organic acid esters, Sensitive to methane, Aromatics compounds, Aliphatic hydrocarbons, Hydrocarbons, Aromatic compounds, Alcohol And organic solvents, Alkenes, aromatic compounds, less polar compounds	(Feng *et al*., 2018)
7	Banana	To predict the quality of banana	MQ-3, MQ-5, M Q-9, MQ-131, MQ-136, MQ-135	(Sanaeifar *et al*., 2016)
8	Royal delicious apple	To predicting the quality of fresh, half and full contaminated Royal delicious apple.	Ethanol, toluene, xylene, Ammonia, (Ammonia and toluene), Alcohol & organic solvent vapor, Hydrogen & carbon monoxide	(Rayappan *et al*., 2018)
9	Citrus Fruits	To detect the presence of Bactrocera dorsalis in citrus fruits	TGS2620, TGS2610, TGS2600, TGS2602, TGS2603, MP901	(Wen *et al.* 2019)
10	Litch	To detect the quality of litch in various atmosphere	PEN3	(Xu *et al*., 2016)

Table 1: Continue

11	Peaches	To discriminate and identify the contamination of fungi in peaches	PEN3	(Liu *et al*., 2018)
12	Wine	To detect the spoilage threshold of wine	MQ-3, MQ-4, MQ-6 (two of each type)	(Rodriguez *et al*., 2019)
13	Tea	To detect appearance and aroma quality of Tea using computer vision and E-nose	PEN3	(Xu *et al*., 2018)
14	Coffee	To classify the coffee samples using E-nose	PEN2	(Yasuo *et al*., 2019)
15	Tea and coffee	To classify the Tea and coffee samples	TGS822, TGS830, TGS825, TGS821, TGS832, TGS826, TGS816, TGS2600, TGS2602, TGS2610, TGS2611, TGS2620	(Omatu and Yano, 2016)
16	Mutton	To detecting adulteration of mutton with duck meat using E-nose	PEN3	(Wang *et al*., 2019)
17	Fish	To classify the different species of fish	TGS 2610, TGS 2620 TGS 830, TGS 880, TGS 2104, TGS 2602, TGS 825, TGS 826,	(Güney and Atasoy, 2015)
18	Pecorino cheese	To classify the cheese using E-nose	SnO_2, (SnO_2 + SiO2), (SnO_2+ Au), (Sno_2+Ag) and (SnO_2+PD) and WO3.	(Cevoli *et al*. 2011)
19	Milk	To detect the adulteration in milk	MQ3, TGS2620 SP3-AQ2, MQ136, TGS822, TGS2602, MQ8, TGS813,	(Tohidi *et al*., 2017)

Table 2: Performances of algorithms

No	Data	Algorithm	Performance
1	Toxic gases from the wastewater treatment plant	PLSR	PLSR with R-square was 0.9967 and Root Mean Square Error (RMSE) 1.17×10^4
2	Air	Support Vector Regression (SVR) and PLSR	SVR provides lower RMSE than PLSR
3	Potato	LDA, SVM, NB, Radial Basis Ensemble	SVM, LDA and Radial Basis Ensemble shows higher accuracy of 100%
4	Moldy Apple	LDA, SVM, BPNN, RBFNN,	BPNN shows higher accuracy with 90% and 72% for group A and group B
5	Herbal medicine	LDA, SVM, DT, KNN, NB, BP	SVM and LDA shows accuracy with 98.94% and 98.34%
6	Cherry Tomato	Single Feed Forward Neural Network, PLS	Single Feed Forward Neural Network shows higher with Higher R^2 and lower RMSE than PLS
7	Banana	PLS, Multiple Linear Regression (MLR) and Support Vector Regression (SVR)	SVR outperforms the MLR with Higher R and lower RMSE
8	Royal delicious apple	PCA and wards method of hierarchical cluster analysis	Both established correlations between samples of apple
9	Citrus Fruits	LDA	LDA show accuracy with 98.21%.
10	Litch	LDA, BPNN, BPNN-PLSR, CCA,	BPNN-PLSR shows better accuracy than other algorithms
11	Peach	PLS-DA	It shows higher prediction rates
12	Tea	KNN, Multinomial Logistic Regression (MLR), SVM	SVM shows higher prediction rate with 100% accuracy
13	Coffee	Common Dimension Analysis (ComDim) and LDA	LDA provides 100% accuracy
14	Tea and Coffee	Learning Vector Quantization (LVQ)	LVQ shows 96% accuracy in four kinds of Tea and 89% in five kinds of coffee
15	Mutton	Linear regressions, Fisher Linear Discriminant Analysis (FLDA), and Multilayer Perceptron Neural Networks analysis MLPN	(MLPN) FLDA and patterns shows accuracy 98.2% and 96.5%,
16	Fish	NB, KNN and LDA	Accuracy of NB, KNN and LDA are 84.73, 80 and 82.4. NB shows maximum accuracy
17	Pecorino cheese	Multi-Layer Perceptron (MLP)	MLP correctly classified the cheese
18	Milk	LDA, SVM	SVM showed accuracy values of 94.64, 92.85 and 87.75% for formalin, hydrogen peroxide and sodium hypochlorite, respectively.

Feature extraction techniques were applied to the datasets to select critical features. Most commonly used feature extraction is PCA.

Kong *et al*. (2019) Proposed a new procedure for feature extraction Weighted Summation (WS). Gaseous pollutants emitted from the pig farm can affect the environment and also a severe impact on the health of humans. They had collected data from pig farm data using E-nose. And they had applied Weighted Summation to datasets. They compared the results with existing feature extraction algorithms and weighted summation showed higher accuracy.

Herrero *et al*. (2016), had proposed classification of water pollutants using wireless portable electronic noses.

Disease Detection Using Electronic-Nose

Detection of soft rot disease in potato (Rutolo *et al*., 2018). In this work, they used WOLF 4.1 (Warwick OLFaction), electronic nose for predicting the contamination of Pectobacterium carotovorum in potato. Data analyzed using algorithms such as LDA, SVM, Naive Bayes, ensemble methods.

Jia *et al*. (2019) suggested PEN3 was used to detect the level of contamination of moldy apple inoculated with Penicillium expansum and Aspergillus niger. Dataset collected from both the apple inoculated with and without bacteria. Four machine learning algorithms were used to analyze the data such as Back Propagation Neural Network (BPNN), SVM and radial basis function neural network (RBFNN), Linear Discriminant Analysis (LDA). They found that the BPNN shows higher accuracy among all the algorithms.

Electronic nose not only detects the human disease but also recognizes the condition in plant and animal (Wilson, 2018). Electronic nose detects the disease based on the Volatile Compound (VOC) emitted from the sample.

Discrimination of Substance Using Electronic Nose

Zhan (2018) suggested a method for discriminating 12 different categories of Chinese herbal medicine using electronic nose. In this work, the electronic nose consists of 16 TGS (Taguchi gas sensors) made in Japan. Data acquired from 600 samples one by one. And they pre-processed the dataset and applied machine learning algorithm such as Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes (NB), Conformal Prediction K-Nearest Neighbour (CP-KNN), Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA). Among them, SVM and LDA show higher accuracy with 98.94% and 98.33%. But the KNN (CP-1NN and CP-3NN) provides the prediction reliability.

Centonze *et al*. (2019) in their paper, they used electronic nose to discriminate the different varieties of oranges belongs to three regions Italy, South Africa and Spain. They applied multivariate statistical models to the E-nose response. And the LDA provides better prediction accuracy.

Fruits and Vegetables Quality Prediction Using Electronic Nose

The freshness of cherry tomato was evaluated in their work (Feng *et al*., 2018). They divided tomatoes into two groups. Two groups of cherry tomato treated with and without high-pressure Argon in the ratio of 0.4, 0.8 and 1.2 Mpa. They used Argon gas as a preservative. And data collected from both groups of tomato. After data acquisition, they used Partial Least Square Regression (PLSR) and Single Layer Feed Forward Neural Network. And they made the comparative study between the two algorithms. Based on the E-nose data, they classified the cherry tomato into four groups.

Jia *et al*. (2019) they inoculated Golden delicious apples with Penicillium expansum and Aspergillus niger. The PEN3 was used to identify the fresh and moldy apples (apples inoculated with Penicillium expansum and Aspergillus Niger). Gas emitted from apple matches with sensors available in PEN3. E-nose response was analyzed using LDA, BPNN, SVM, Radial Basis Function Neural Network (RBFNN). BPNN provided the best accuracy among all methods. E-nose identifies not only fresh apple and but also discriminated moldy apples inoculated with Penicillium expansum and Aspergillus niger.

Brezmes *et al*. (2000) suggested a method for monitoring fruit ripeness using E-nose. For this purpose, they used Peach, Apple and Pear. They observed the fruit from the day of harvest until it became overripe. They used the neural network to classify the fruits into different stages of green, ripe and overripe. Peach and Pear shows higher accuracy than Apple.

Rayappan *et al*. (2018) proposed a method for predicting the quality of fresh and contaminated Royal delicious apple. E-nose consists of six readymade sensors and integrated into a single circuit. E-nose values recorded at the sample time of 1s. They applied PCA and the ward's method of cluster analysis to data. This method found a correlation between the different stages of apple.

Wen *et al*. (2019) sweeping E-nose was used to identify and detect the presence of Bactrocera dorsali in citrus fruits. They applied PCA and LDA to the E-nose data. They found that LDA provides better performance with an accuracy of 98.21% and discriminate the different stages of incubation and invasion.

Xu *et al*. (2016) used PEN3 E-nose predicts to litch quality. Litch quality was detected in different environments (normal temperature, refrigerator, controlled condition). The hardness of the litch sample was obtained from E-nose. LDA, Canonical Correlation Analysis (CCA), BPNN and BPNN- Partial Least Squares Regression (BPNN-PLSR), were employed to sensor data. They found that BPNN-PLSR effectively predicted hardness of litchi under refrigerator storage conditions and a controlled-atmosphere environment, but it was poor in normal storage.

Liu *et al*. (2018) proposed method for identifying fungal contamination in peaches using a PEN3. Peaches were inoculated with spoilage fungi such as Botrytis cinerea, Monilinia fructicola and Rhizopus stolonifer and then stored for long periods. E-nose was used to analyze volatile compounds generated in the fungi-inoculated peaches. Data pre-processing was done by Standard Normal Variate(SNV) to eliminate the signal drift. PLSR was applied to classify the fungi species. They successfully discriminated Peach sample inoculated with fungi after 48hours of storage. The statistical results showed Volatile compounds of peach was affected by the total count and species of fungi.

Sanaeifar *et al*. (2016) suggested E-nose for predicting the properties of banana. They made the comparison between E-nose response data and quality indices of banana was applying by Partial Least Square, Multiple Linear Regression and Support Vector Regression. They found pH and Titratable Acidity of quality indices of banana showed poor correlation with E-nose response.

They found that the quality indices of banana predicted using SVR were better than other algorithms. They discovered that E-nose was reliable to predict the properties of banana.

Quality Prediction of Beverages

Electronic nose provides an efficient method for checking the quality of beverages. (Rodriguez *et al*. 2019) Suggested design for identifying wine quality is analyzed using the electronic nose. E-nose response of wine collected at the sampling frequency of 18.5 Hz during 180 seconds. And they classified the dataset into high quality, average quality and low quality. They identified the threshold of wine quality.

Xu *et al*. (2018) Proposed a method for predicting the quality of Tea by E-nose and Computer Vision System (CVS). E-nose was used to categorize the quality of Tea based on the aroma. CVS analyzed the appearance of the Tea; it captures the image of Tea and extracts information such as size and color. They made a comparison between E-nose signals and CVS signals. They developed the data fusion strategy combining both the methods of E-nose and CVS to predict the quality of the E-nose.

Yasuo *et al*. (2019) proposed a method to analyze the coffee sample of six types using PEN2 (seven MOS sensors). Common dimension analysis was used to reduce the large datasets and LDA was applied to classify the samples. This method is efficient to classify the coffee samples.

Omatu and Yano (2016) Designed the E-nose (14 sensors) system to discriminate Tea or coffee based on aroma emitted from the samples of different concentrations. They used the Learning Vector Quantization neural network to analyze the data. After reducing the E-nose noise, obtain the maximum value of odor. Normalize the datasets; values were affected due to different concentration level. E-nose, along with learning vector quantization neural network was efficient to discriminate between Tea or coffee.

Electronic Nose in Animal Food Analysis

Animal foods are highly perishable. Electronic nose used to detect the quality and identify the adulteration of animal food. In their study, (Wang, 2019) suggested a method for detecting adulteration of mutton with duck meat using E-nose. They performed Multivariate data analysis by using linear regression, Fisher Linear Discriminant Analysis (FLDA) and Multilayer Perceptron Neural Networks analysis (MLPN) on E-nose signals.

Güney and Atasoy (2015) designed the E-nose (8 sensors) to discriminate between different species of fish. After data acquisition, data pre-processing was done by signal pre-processing, normalization and feature extraction. The proposed Hybrid algorithm shows higher accuracy when compared to all methods KNN, NB, LDA.

Electronic Nose for Edible Oil

Nowadays, E-nose can also be used in detecting the quality of the oil. (Majchrzak *et al*., 2017) proposed method for determination of the product's geographical origin and further in the detection of adulteration as well as deterioration caused by external factors. E-nose used to discriminate between non-oxidized and oxidized oils. They used Cluster Analysis (CA), PCA and LDA to E-nose data. LDA produced better results than CA and PCA in discriminating between oxidized oil and non-oxidized oil.

Upadhyay *et al*. (2017) designed the E-nose (18 Metal Oxide Semiconductor sensors) used for monitoring the disposal time of deep-fried sunflower oil stabilized with natural oxidants.

Rapeseed is one of the sources of edible oil (Gancarz *et al*., 2017) agrinose used for detecting the quality of rapeseed. Agrinose(eight MOS sensors), sensors were selected based on lower power consumption, low susceptibility to humidity and temperature. The quality of rapeseed was detected using E-nose during 31 days of storage was studied. Agrinose used for the examination of Colony Forming Unit, Ergosterol content, Fourier Transform Infrared Spectroscopy and Volatile Organic Compounds. Agrinose monitored the microbiological count of rapeseed during the first twelve days of storage. PCA had shown a correlation between Ergosterol content, sensor response, Colony Forming Unit and the type of microflora.

Electronic Nose in Dairy Product

E-nose provides the best quality assessment of the dairy product. It is used to detect the adulteration in milk and classify the cheese according to manufacturing techniques.

Cevoli *et al*. (2011) proposed E-nose to classify the pecorino cheese. They used ANN and E-nose data feed as input to the ANN. After feature extraction using PCA, feed the features to the ANN. They made a comparison between the before and after feature extraction. Before feature extraction, it showed higher accuracy. Feature extraction was not efficient in this method.

Tohidi *et al*. (2017) suggested a technique using the electronic nose to detect adulteration in raw milk. After data acquisition, data pre-processing involves steps such as baseline correction, compression and normalization. PCA was used to reduce the dimensionality of data. They used multivariate data analysis such as LDA, SVM to analyze E-nose. SVM showed higher accuracy. This method found the adulteration and percentage of adulteration by using chemometrics.

Conclusion

In this review, we have given a summary of E-nose applications in various fields, finding the adulteration in mutton, milk and predicting the quality of fruits. It can also classify the food based on the aroma emitted from food. Most of the classification techniques provide more than 90% accuracy. Among them, SVM and LDA provide 100% prediction rate and Support Vector Regression provides lower RMSE and higher R^2. BPNN delivers the desired performance in most of the cases.

Acknowledgement

We wish to express our sincere thanks to Sastra Deemed To be University for providing facilities.

Author's Contributions

Literature review and drafting was done by B. Santhi and Manuscript was written by S. Keerthana.

Ethics

There is no ethical issues in publishing the paper.

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