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Applications of electronic nose and machine learning models in vegetables quality assessment: A review

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***Abstract*—Vegetables are an integral part of a balanced diet. They are good source of nutrition enriched with vitamins, mineral and antioxidants. They are prone to spoilage after harvesting without proper storage. Their quality can be determined by chemical analysis, high-performance liquid chromatography and near-infrared detection method. These methods are time taking, required a high cost equipment and trained person to perform. This article discussed the basic concept of electronic nose and machine learning. Electronic nose is used to detect gases excreted from vegetables and produced electronic signals. Machine learning is trained on these signals and predict the quality of vegetables. This paper presents the application of an electronic nose system with machine learning models. It is studied that this method is a cost-effective, portable and potential upcoming technique to overcome quality issues in vegetables.**

***Index Terms*—Vegetable, Electronic Nose, Machine Learning, Quality, Diseases**

I. Introduction

Vegetable are a good source of vitamins, minerals, fibers and antioxidants and prevent humans from different diseases. Vegetable flavor is influenced by pre-harvest, harvest, post-harvest and genetic factors. The flavor of vegetables start perishing as time between harvest and consumption increases. If proper storage is not used then these vegetable get rotten partially or completely. Different techniques can be used for qualitative analysis. One of the method; chemical analysis is a widely used method to detect the quality of vegetables, but it is a destructive testing method and has low efficiency. With the advancement in technology, high-performance liquid chromatography, near-infrared detection, spectrophotometry, gas chromatography and other analytical techniques have been applied to detect the quality of vegetables [1]. These techniques are time taking and required huge resources and are usually not accessible at the line in industries. Sensory evaluation techniques are commonly used to assess the quality of fresh vegetables. The testing is normally carried out by trained persons using the sense of touch, smell and sight [2], but the result can be affected by physical conditions, the external environment and the emotions of the sensory personnel making it is difficult to do accurate qualitative judgement [3]. Keeping this in view, it is need of the time to develop a method that is cost-effective, accurate and simple to monitor the quality.

The term electronic nose appeared in early 1990s. The electronic nose (enose) is defined as the instrument consisting of an array of chemical sensors that have the capability of recognizing simple and complex odours [4]. The key principle involved in the enose system is the transfer of aroma on an array of sensors that provide signals dependent on sensor sensitivity and the aroma produced by the eatable product [5]. Compared to the human nose, enose is faster, more reliable, not influenced by environmental factors, less biased and has more sensitivity.

In the last decade, machine learning emerged as a powerful tool that can solve complex problems on its own using enose data. Machine learning is a technique that enhances the performance of a system by learning from experience through the computational method. This allows for more informed decision making and action to be taken in real world scenarios with nominal human interference [6]. The common machine learning technique used in our literature review are principle component analysis (PCA), linear discriminant analysis (LDA), artificial neural network (ANN), support vector machine (SVM) discriminant function analysis (DFA), Probabilistic Neural Network (PNN).

Enose coupled with machine learning (ML) models is a novel nondestructive technique to monitor the quality of vegetables and getting better and more advanced day by day. Figure 1 shows the working of typical enose system for quality evaluation. This article reviewed the progress of enose and ML models application on broccoli, onion, potato, pepper, spinach and tomatoes mostly in the last five years. Table 1 summarises the studies discussed in this literature review.

II. Application of Electronic Nose and Machine Learning on Vegetables

A. Broccoli

Broccoli is a rich source of minerals, vitamins and antioxidants. Broccoli has many health benefits, it reduces the chance

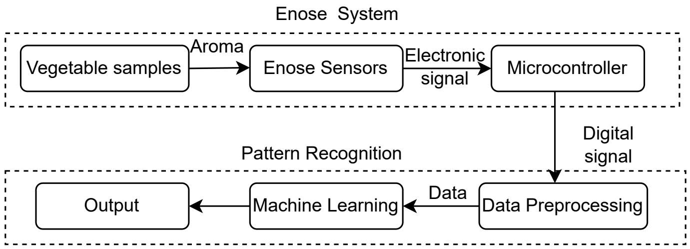

Fig. 1. Working of Electronic Nose System.

of cancer, improves bone health, reduces inflammations and protects against cardiovascular diseases [7].

In a study, fresh broccoli, half-contaminated broccoli and contaminated broccoli samples were purchased from the local market. Six Taguchi series sensors namely: TGS 822, TGS 826, TGS 880, TGS 2600, TGS 2602 and TGS 2620 based enose were employed to collect data. PCA shows a significant difference among samples [8].

In another study, Fresh broccolis was purchased free from physical damage. An iNose (type of enose) was used to collect the aroma profile. Broccolis were divided into fresh, medium fresh and spoiled. Samples on day 0 and 3 are classified as fresh, days 6 and 9 as semi-fresh and days 12 and 15 was classified as spoiled. Canonical discriminant analysis was able to classify with great accuracy of 100%. PCA shows a cumulative variance of 95.37% [9].

Broccoli's were harvested 91 days after planting. Broccoli heads were soaked in distilled water (control group) and in water containing 2mg/kg selenite (SE treatment). The broccolis were then stored at 0°C and 20°C. The effect of selenite treatment was analyzed. PEN 3 enose system was used to collect data. PCA was used and the accumulative variance of 98.07% at 0°C and 99.97% was achieved at 20°C [10].

B. Garlic

Garlic is a bulbous plant consumed as a vegetable. It is a rich source of nutrient and prevent dementia, Alzheimer's and reduce the risk of cardiovascular diseases [11], [12].

Fresh garlic cultivars were purchased namely Lamphun, Uttaradit and Chiang Mai. The electronic nose system used to collect varietal difference data consists of MQ2, MQ135, TGS822, TGS826, TGS2600, TGS2602, TGS2611 and TGS2620. PCA analysis shows a cumulative variance of 99% and it can seem that enose clearly discriminates the varietal difference [13].

Garlic scapes of different cultivars namely: Morado, Gostoso, Fuego, Sureno and Castano were harvested. The electronic nose system α-Prometheus was used to collect data. This device has two units, one is a sensor array system that is FOX-4000 while the other is a fingerprint mass spectrometer α-KRONOS. Using discriminant function analysis (DFA), fresh garlic was classified with an accuracy of 86.7%. Garlic was further cut and stored at $5°C$ for 3 days. DFA correctly classified samples in Gostoso, Fuego and Sureno cultivars with a correct classification rate of 100% in their respective group. In Morado and Castano cultivars, DFA was able to classify it with 77.8% accuracy in both cases in their respective group *i.e.* fresh and stored. [1].

C. Onion

Onion has great economic value and is cultivated throughout the world as it enhances the flavor of food. It has vitamins, flavonoids and organosulphur compounds which protect against cancer, diabetes, cardiovascular diseases and ageing [14].

Forty healthy onion were purchased and examined thoroughly to ensure the absence of any physical, microbiological damage. Twenty onions were then inoculated with *Fusarium oxysporum* f.sp. *cepae*. Onion were then classified into sever diseased, mild infected and non infected. Pen 3 enose was used to collect data. KNN, LDA, SVM were used as classifcation model and the accuracy obtained were 89.60%, 89.60% and 87.50% respectively [15].

Ghosh carried a research on the detection of fresh and stale onions. Enose used consist of following sensors namely: TGS 813, TGS 821, TGS 826, TGS 832 and TGS 2611. PNN was used as classification model and the accruacy acheived was 93.06% [16].

In a study conducted by Konduru *et al.* Enose was employed to collect data from onions. LDA was used to classify the onion as a healthy or diseased group. Enose assembled consisted of different sensors namely: SB-11A, SB-AQ8, TGS 813, TGS 822, TGS 825, TGS 826 and TGS 2620. The correct classification rate was 89.6% using LDA [17].

The author also worked on two groups of jumbo yellow onions. The onion selected were free from bruises and damage. To prevent plant pathogens harbored on the dry skin, the dry skin of the onion was peeled off and the surface of the bulbs was sterilized with 70% ethanol solution and allowed to stand for 10 minutes before washing with distilled water to remove chemical residue. The onions were then dried by placing them at room temperature for one hour. *Burkholderia cepacia* inoculum was injected into the neck of the onion on opposite sides. Enose was used to collect data from bacterial infected and control group onions. The enose that was used consisted of SB 11A, SB-AQ8, TGS 813, TGS 822, TGS 825, TGS 826 and TGS 2620 sensors. Using all sensors, the classification accuracy of 85% was achieved by SVM [18].

Three local types of Tropea red onion (Tonda, Mezza Campana, Allungata) and one red onion cultivar were analyzed using ISE Nose 2000 enose system. Onions were grown in the same field so that evaluation was not affected by cultural practices or environmental factors. Clear separation among four groups was achieved with DFA and the overall classification rate was 97.5% [19].

D. Potato

Potato is the fourth largest food crop in the world and is regarded as the food of the future. The potato industry has great significance in ensuring food safety and improving

TABLE I
SUMMARY OF THE STUDIES BASED ON ELECTRONIC NOISE AND MACHINE LEARNING

Detection	**Enose Used**	**Detection Technique**	**Result**	**Year**	**Ref**
Broccoli					
Spoilage	iNose	Canonical discriminant analysis and PCA	100% accuracy & 95.37 total variance	2019	[9]
Selenite effect	PEN 3	PCA	Total variance of 98.07% at 0C & 99.97% at 20C	2017	[10]
Garlic					
Cultivar difference	Self made	PCA	99% cumulative variance	2015	[13]
Cultivar difference	\alpha-KRONOS	DFA	86.7% accuracy	2014	[1]
Onion					
Fungus Detection	PEN 3	KNN, LDA, SVM	89.60%, 89.60% & 87.50%	2022	[15]
Freshness	Self made	PNN	93.60%	2022	[16]
Disease detection	Self made	LDA	89.6% accuracy	2015	[17]
Bacterial infection	Self made	SVM	85% accuracy	2015	[18]
Cultivar difference	ISE Nose	DFA	97.5% accuracy	2013	[19]
Potato					
Freshness	Self made	PNN	90.92%	2022	[16]
Varieties difference	Self made	LDA & ANN	100% & 98% accracy	2021	[20]
Soft rot detection	WOLF 4.1	Random Forest & LDA	100% accuraies	2017	[21]
Soft rot detection	Self made	SVM & radial basis function neural network	83.35% & 80.6% accuracy	2018	[22]
Pepper					
Pepper classification as sweet or spicy	Self made	ANN, Nu-SVM, C-SVM	100% accuracies	2022	[23]
Freshness assessment	Inose	PCA	98.48% total variance	2018	[24]
Spinach					
Freshness assessment	Self made	SVM & back propagation neural network	75% & 81.25% accuracy	2019	[25]
Tomato					
Treatment effect	PEN 3	K nearest neigbor	100% accuracy	2018	[26]

agriculture economics [20]. Potato is a good source of vitamin C, vitamin B6 and dietary fiber [21].

Potato freshness was detected using Enose. The enose comprised of TGS 816, TGS 823, TGS 825, TGS 832, TGS 2611. Potato was classified into fresh and stale. PNN was used to classify and 90.92% accuracy was acheived [16].

Five varieties of potatoes namely Sprite, Sante, Agria, Jelly and Marfona were purchased. Enose was used to collect data. Enose used in this study comprised of following sensors: MQ3, MQ4, MQ8, MQ9, MQ135, MQ136, TGS813, TGS822 and TGS2620. ANN and LDA were employed to classify the potato variety based on enose data. LDA achieved 100% accuracy while ANN was a bit on the lower side which is 98% [22].

Soft rot in potatoes caused by *Pectobacterium carotovorum* was detected by WOLF 4.1 enose system. 80 potatoes of good quality were purchased and split evenly. 40 samples were then incubated with the bacterium and tested at pre-symptomatic and symptomatic time points. Both random forest and LDA achieved overall 100% accuracy in classification [23].

Soft rot in potatoes caused by the erwinia pathogen of carrot soft rot was detected. Six levels of disease were studied. Level 1 was normal, level 2, 3, 4, 5 and 6 had 0-15%, 15-30%, 30-50%, 50-70% and 70-100% diseased tuber, respectively. Enose used consisted of TGS series sensors that is TGS 2600, TGS 2602, TGS 2610, TGS 2611 and TGS 2620. Radial basis function neural network had classified all levels with an accuracy of 73.1%, 74.8%, 81.2%, 83.1%, 87.5% and 84.3% respectively from levels 1 to 6. SVM obtained higher accuracy than radial basis function neural networks with an increase of 5.5%, 4.4%, 0.5%, 3.5%, 2.9% and 2.2%. The overall accuracy of radial basis function neural network and SVM were 80.6% and 83.85% respectively [24].

E. Pepper

Pepper is one of the most consumed vegetables worldwide. It contains high amounts of vitamin A, C and minerals. Consumption of 60-80 grams of pepper can provide 100% of vitamin C and 25% of vitamin A of the daily body requirements. In addition, it has other health-promoting substances like flavonoids, carotenoids and polyphenols [25].

Pepper was classified as sweet or hot in terms of its food properties depending on the capsaicin [26]. Padron variety of pepper was studied. Sweet and spicy varieties were determined using an enose system. Enose consisted of TGS813, TGS822, TGS2620, MQ3, MQ4, MQ8, MQ9, MQ135 and MQ136 sensors. SVM and ANN techniques were performed on sensors output data. ANN classified sweet and spicy pepper with 100% classification rate and R^2 value is 0.99. Nu-SVM and C-SVM method was also used to classify the two categories and gave 100% accuracy with linear, polynomial, radial and sigmoid kernel function [27].

Freshness assessment of green bell pepper was carried out using an enose system. Days 0, 1, 3 and 5 are regarded as fresh and days 7 and 9 are regarded as spoiled. Green bell pepper physiologically matured were purchased and cut into pieces. Enose named iNose was employed to collect the data. Partial least square and PCA were used for the analysis of data. Partial least square gave R^2 0.9783 while PCA shows a cumulative variance of 98.48% [28].

F. Spinach

Spinach is a perishable vegetable and contains a high amount of vitamins, minerals, carotenoids and phenolic compounds [29]. Spinach of similar size and maturity were harvested and packed in humidity control bags at 4°C. Enose was used to conduct analysis each day and lasted for 12 days. It consisted of the following sensors TGS 822, TGS 826, TGS 825, TGS 831, TGS 2600, TGS 2610 and TGS 2611. SVM and backpropagation artificial neural network were used for the classification of freshness and achieved 75% and 81.25% accuracy respectively [30].

G. Tomato

Tomato is one of the most consumed and cultivated vegetables around the globe owing to its delicious taste and nutrient profile [31]. Tomato intake has been proven to be an anticancer agent, boost the immune system and prevent blood from clotting [32]. Tomatoes free from any defect were harvested at the light red maturity stage. Tomatoes were further divided into three groups that were at chilling storage (CS), blanching treatment (BT) and control group. Tomatoes from CS group were refrigerated at 5°C for one week and assessed at 0, 3 and 7 days. BT tomatoes were further dived into two groups. One group is blanched at 50°C while the other group is blanched at 100°C for the same time of one minute and was assessed right after blanching. Control group tomatoes were stored at room temperate and were assessed at 0, 3 and 7 days. PEN 3 enose was used for the detection of aroma. K nearest neighbor was used to classify and it had splendid accuracy of 100% for all the groups [33].

III. Conclusion

This study identified and evaluated enose and ML models for the quality evaluation of vegetables. The use of ML models with enose within the context of quality evaluation of vegetables is still in the early stages but increasing rapidly. The productivity of enose results from the smart selection of sensors for the detection of volatile compounds. The classification accuracy of the studies are high, indicating that ML with sensors data offers a promising method for the quality assessment of vegetables. The use of enose with ML discussed in this review is a commitment to reduce the shortcomings of other analytical instruments. New discoveries in gas sensors and their operations will increase the expansion of enose technologies and yield solutions to solve problems arising in the food and agriculture industries. Utilization of advanced enose devices with ML techniques will lead to the greater ability for sensing tools as well as providing quality inspection of agricultural and food products in a rapid and more consistent procedure.

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