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Review Article

APPLICATION OF ELECTRONIC NOSE AND MACHINE LEARNING IN DETERMINING FRUITS QUALITY: A REVIEW

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ABSTRACT

Fruits are an essential part of our diet, providing necessary nutrients that promote good health and proper functioning of our bodies. However, determining fruit quality can be complex due to numerous factors such as harmful insects, fungal diseases and damage caused during the harvesting and transport processes. Current methods employed by industries, such as sensory panels for categorising damage from healthy produce; are not as precise as needed. Therefore, there is a pressing need for a more simple and accurate way to assess the quality of fresh produce. An emerging technology, the electronic nose, presents a cost-efficient and precise solution to this problem. The electronic nose identifies various aromas which helps to evaluate fruit quality. In correlation with this, machine learning models classify fruits into their respective grades using the data collected by the electronic nose. In this review, we delve into the practicalities of using the electronic nose technology and machine learning algorithms to identify the quality of various fruits such as apples, bananas, peaches, litchis, strawberries, and pomegranates. In conclusion, the integration of the electronic nose technology and machine learning models could revolutionise the fruit industry by providing an efficient, precise, and cost-effective method for determining fruit quality.

Keywords: Electronic nose, Machine learning, Fruits, Diseases, Quality.

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INTRODUCTION

Fruits comprise essential nutrients and provide us with vitamins, dietary fibre, and an array of micronutrients required for the proper functioning of our bodies. There is considerable proven evidence of public health nutrition associated with their consumption. Consumption of fruits is recommended by many organisations such as the World Health Organization (WHO), Food and Agriculture Organization, European Food Safety Authority, and United States Department of Agriculture, owing to the health benefits provided by the high levels of micronutrients and fibres (Boeing *et al.,* 2012). Different research had confirmed the preventative and treatment effects of fruits on human diseases like heart disease, hypertension, and stroke (Baietto and Wilson, 2015).

The demand for quality evaluation of fresh produce has rapidly increased in the last decade due to hygiene and safety considerations in the food supply chain. Moreover, consumers are more conscious about the quality of the products they consume. Chemical analysis is used to detect the quality of produce, which results in sample damage, extended testing durations, complex procedural operations, and an inability to achieve real-time detection. Near-infrared spectroscopy and hyperspectral imaging have emerged as non-destructive physical detection methods, but their effectiveness can be masked by the spectral changes induced by the physical attributes of food. The quality evaluation of agricultural and food products still relies on routine processes based on consumer preferences through sensory evaluation and individual satisfaction levels. The consumer's personal preference is subjective towards palatability, which varies in terms of taste, flavour, and aroma. A strong relationship between product quality and fruit aroma can attract consumer preference (Stiletto and Trestini, 2021). In this regard, an odour or smell indicator that could mimic the application of the human nose can become a sensing tool to replace conventional methods. Further combining electronic nose technology with machine learning enhances its odour recognition capabilities, enabling more precise and versatile odour analysis (Anwar *et al.,* 2023a, Anwar *et al*., 2023b).

The term electronic nose (e-nose) first appeared at the beginning of the 1990s (Gardner and Bartlett, 1994). E-nose is a combination of gas sensors that mimics the human nose. Rapid sensing is achieved by these gas sensors with a relatively lower price compared to different analytical equipment like laser scattering analyzer, gas chromatography-mass spectrometry, and high-performance liquid chromatography (Bushdid *et al.,* 2014). E-nose is less biassed and gives more accurate results when compared to the sensory panel. E-nose has wide applications in determining food quality, such as processing quality, sensory attributes, and microbiological properties. Much attention has been given to use e-noses for evaluating the quality of food such as meat, tea and spices. This review mainly targets the application of e-nose systems in fruits in the last decade.

Electronic nose: Human nose is a useful tool for assessing the quality of fresh produce. The human nose has 400 scent receptors and can distinguish between one trillion smells, but it is not always precise and can be biassed (Zhong, 2019). Moreover, the mental and physical condition of humans can affect the evaluation. Additionally, the human nose has a limited detection limit and cannot sense toxic odourless gases. These limitations do not allow the human nose to be a universal tool for all smell-related classifications.

E-nose has become an emerging technology in recent years due to its wide range of advantages, such as easy operation, quickness, low cost, and real-time detection. E-nose is an apparatus that analyses and recognizes complex gases (Anwar and Anwar, 2021). The key principle involved in e-nose is the transferring of the headspace gas to sensors. In return, the sensors provide signals that depend on the sensors' selectivity and the volatile compounds present in the headspace. E-nose sensors can be classified into several types depending on the sensing material. These types include metal oxide semiconductors, conducting polymers, surface acoustic waves, and quartz crystal imbalance sensors (Wilson, 2012). Metal oxide semiconductor-based e-nose is mostly exploited in the food industry. Figure 1 shows a typical working of an e-nose system.

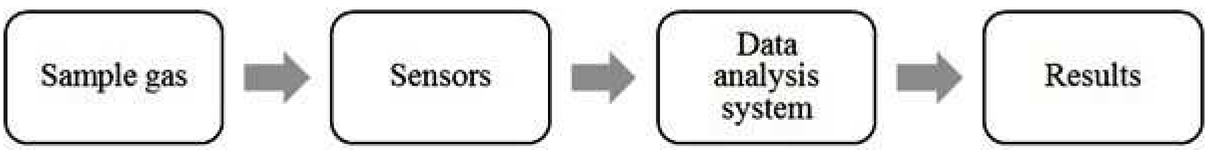

Figure 1 Working of e-nose system.

Machine Learning: In 1959, the phrase "machine learning" was first used. It refers to the capability of computers to learn on their own, without needing to be programmed for a particular task. In the recent past machine learning (ML) has emerged with high-performance computing and big data technologies to create new opportunities to investigate, quantify and understand data-intensive processes in agriculture. ML involves a process to learn from experience (training data) to perform a task (Sharma *et al.,* 2020). In ML, data consists of a set of examples and is described by a set of attributes known as features or variables. Various mathematical and statistical models are used to calculate the performance of ML models. After the end of the learning process, the trained model is able to predict and classify new examples (testing data) using the experience obtained during the training process (Greener *et al.*, 2022). Figure2 shows a typical ML approach.

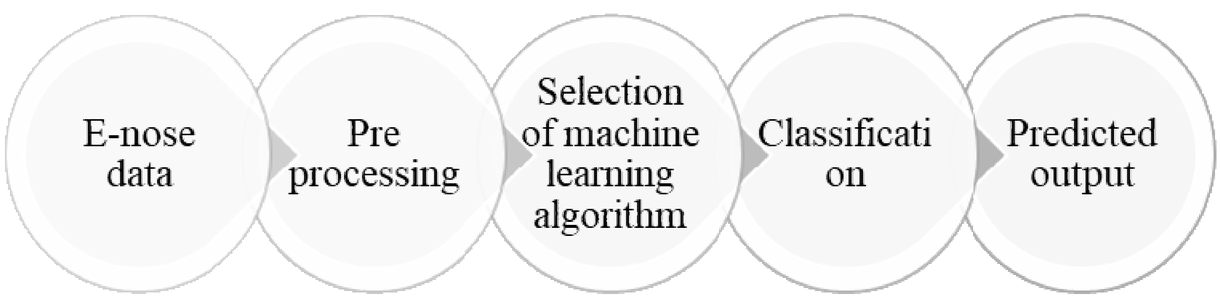

Figure 2 Typical flow of machine learning algorithm.

ML is classified into different categories depending on the learning type: supervised machine learning (SML) and unsupervised learning models. SML consists of labelled data sets to train the algorithm and predict the result. SML is further categorised into two types that are classification and regression. In classification, a model is trained to predict discrete or categorical output variables while regression deals with the problem of predicting a continuous variable. In food, mostly SML models are used. In unsupervised machine learning, models aim to find the underlying structure and patterns within unannotated data (Rajoub, 2020). Support vector machine (SVM), random forest (RF), K-nearest neighbour (KNN), decision tree (DT), stepwise discriminant analysis (SDA), multilayer perceptron neural network (MLPN), back propagation neural network (BPNN), linear discriminant analysis (LDA), partial least square discriminant analysis (PLS-DA), principal component analysis (PCA), least square support vector machine (LS-SVM) and partial least square regression (PLSR) are commonly used machine learning models in food and agriculture sector.

Application of Electronic Nose in Fruits: E-nose was applied to different fruits like apples, bananas, peach, litchi, strawberry and pomegranate and the studies are summarised in Table 1.

Apple: Many countries in the world regard apples as a high-demand consumer fruit due to their good ecological adaptability, good shelf life and high nutritional value. Apple is one of the most nutritional foods owing to its organic acids, vitamins, minerals, dietary fibres and polyphenols (Musacchi and Serra, 2018). Detection of apple quality is crucial in terms of the food industry.

Three levels of apple quality are determined using e-nose. Grade 1 denoted it with no external stab wound, crushed wound, broken skin, insect wound, disease wound, shrinkage or rot and has a smooth and rosy surface while on the internal side no rot, dryness or shrinkage. Grade 2 had slight skin damage, stab wounds, black spots and frostbite and had no shrinkage, rot or dryness inside. Grade 3 apple surface was damaged with pests and diseases and had decay or shrinkage outside with shrinkage, dryness and rot inside the apple. Self-made e-nose system was used consisting of MQ2, MQ3, MQ6, MQ8, MQ9 and MQ135 sensors. A proposed KNN-SVM was used to classify and predict the outcomes. KNN algorithm was used to select the K value from the training samples that were nearest neighbours of the sample to be tested. If the K values belong to the same category, the sample tested belongs to that category, otherwise SVM model was used on K sampled value. The researcher achieved an accuracy of 97.78% from this method. KNN, RF, DT and SVM were also used and the accuracy rate achieved was 93, 93, 91 and 83% respectively (Zou *et al.*, 2022).

Apples were purchased based on uniform size and maturity and then selected for further treatment. One group was taken as a blank group and another group was inoculated with mould *Penicillium expansum.* Each apple was drilled three holes at different points and *Penicillium expansum* suspension was inoculated into the hole. When the apple started to decay, it was further separated into three groups based on the size of the rotten spot. These sizes were 0.5-1 cm, 1.0-1.5 cm, and 1.5-2.0 cm in radius. PEN3 e-nose was employed to collect volatile compounds. LDA, KNN achieved similar accuracies of 95.83% while PLS-DA had 93.75% (Guo *et al.*, 2020).

Ripening agents are used for the artificially ripening of fruit but the fruit flavour and quality are not the same as those of naturally ripened fruit. E-nose with 12 sensors namely TGS2600, TGS2602, TGS2603, TGS2610, TGS2611, TGS 2612, TGS2620, GSBT11, WSP2110, MS1100, MP135, MP901 was used to detect the ripening method of carb apple. RF gave an accuracy of 98.3% while SVM achieved 97% accuracy. PLSR shows the R^2 was higher than 0.91 (Qiao *et al.*, 2022).

Fuji apples were purchased at their optimal condition and were selected on the basis of uniformity of colour, size and weight as well as free from mechanical damage or any defect. The apples were then divided into four groups, one was used as a control group and the other three groups were subjected to a drop test. In the drop test, apples were dropped from the height of 0.20, 0.50 and 0.80 metres respectively and were caught immediately after the bounce to prevent additional injury. PEN3 e-nose was used to collect the volatile compounds. The overall accuracy of the four groups using SDA was 97.5% for training and 93.8% for testing. MLPN showed overall accuracy of 100% while BPNN had an excellent correlation ($R^2 > 0.98$) with classification values for damaged apples (Ren *et al.*, 2018).

Banana: Banana is an important component of a healthy diet and aids in the retention of calcium, phosphorus and potassium in the body. Bananas neutralise the acidity of gastric juice and help in reducing ulcers by coating the lining of the stomach (Kumar *et al*.,2012). There has been very little work in the past decade to detect banana quality using the e-nose system and still there is a major gap to cover.

Banana was categorised into ripe, unripe and rotten bananas. E-nose used to collect data consist of TGS812, TGS822, TGS826, TGS2600, TGS2602, TGS2611, MICS5524, MQ2, MQ4, MQ5 and MQ136 sensors. BPNN was used to classify the ripeness level with 100% accuracy (Hendrick *et al.*, 2022).

Peach: Peach is a fruit of high nutritional and economical value. Carbohydrates, dietary fibres, organic acids, polyphenols, minerals and vitamins are provided by peaches which in turn has a beneficial effect on human health and improves heart health and boosts the immune system (Stojanovic *et al.*, 2016).

E-nose was used to classify peach growth phases. The E-nose was equipped with 13 sensors, 9 of them were from the MQ series while 4 were from the TGS group. The sensors used were MQ2, MQ3, MQ4, MQ5, MQ6, MQ7, MQ8, MQ9, MQ135 and TGS822, TGS2600, TGS2602, TGS2603. The measurement was taken in 4 stages, 3 pre-harvest and 1 post-harvest, stage 1: 0-35 days, stage 2: 36-49 days, stage 3: 51-70 days and stage 4: 71-100 days. All the days were after full bloom.

Table 1 shows the type of e-nose employed, technique used and results achieved

Detection type	E-nose employed	ML Techniques	Results (Accuracy)	Authors
		Apple		
Disease	Self-made	KNN-SVM	97.78%	(Zou *et al.*, 2022)
		KNN	93%	
		SVM	93%	
		RF	91%	
		DT	83%	
Disease	PEN 3	LDA	95.83%	(Guo *et al.*, 2020)
		KNN	95.83%	
		PLS-DA	93.75%	
Ripening method	Self-made	RF	98.3%	(Qiao *et al.*, 2022)
		SVM	97%	
Damage	PEN 3	MLPN	100%	(Ren *et al.*, 2018)
		SDA	93.8%	
		Banana		
Ripeness level	Self-made	BPNN	100%	(Hendrick *et al.*, 2022)
Ripening and senescence stage	Self-made	Back-propagation multilayer perceptron neural network	97.33% for ripening and 94.44% for senescence	(Sanaeifar *et al.*, 2014)
		Peach		
Growth phase	Self-made	SVM	98.08%	(Voss *et al.*, 2019
		RF	96.15%	
		KNN	92.31%	
		ELM	61.54%	
Detection of different fungi species	PEN 3	PLS-DA	90%	(Liu *et al.*, 2018).
Spoilage detection	Fox 4000	MFRG	77.22%	(Huang *et al.*, 2017)
		LS-SVM	74.68%	
		PLSR	61.18%	
Mechanical damage	Self-made	LS-SVM	77.88%	(Yang *et al.*, 2020)
		PLSR	74.44%	
		Litchi		
Mechanical injury	PEN 3	KNN	91.43%	(Xu *et al.*, 2020)
Freshness evaluation in different environments	PEN 3	BPNN	89.33% for room temperature and 100% for both refrigeration and controlled environment.	(Xu *et al.*, 2016a)
Variety difference	PEN 3	SVM	92%	(Xu *et al.*, 2016b)
		Strawberries		
Mechanical damage	FOX 4000	PLS-DA	92.1%	(Cao *et al.*, 2022).
Mechanical damage	FOX 4000	LS-SVM	90.88%	(Rao *et al.*, 2020)
		PLSR	91.66%	
Freshness	PEN 3	PLS-DA	92.3%	(Xing *et al.*, 2018)
		SVM	96.2%	
Fungus detection	PEN 3	MLPN	100% for the control group and *Penicillium* species, 93.3% and 96.6% for *Botyris* and *Rhizopus* Species	(Zhu *et al.*, 2013).
		Pomegranate		
Fungus detection	Self-made	BPNN	100%	(Nouri *et al.*, 2020)
		SVM	90%	
Varieties detection	Self-made	LDA	95.2%	(Sanaeifar*et al.*, 2016)

Four supervised machine learning models were employed namely extreme learning machine (ELM), SVM, KNN and RF. Extreme learning machine classifier had the lowest accuracy which was 61.54% while SVM, RF and KNN had achieved a good accuracy rate of 98.08%, 96.15% and 92.31% respectively (Voss *et al.*, 2019).

An E-nose made of MQ3, MQ5, MQ9, MQ131, MQ135 and MQ136 gas sensor was used to collect data from bananas during the ripening and senescence stage. Back-propagation multilayer perceptron neural networks classify the ripening stage and the senescence stage at 97.33% and 94.44% accuracy respectively (Sanaeifar *et al.*, 2014).

Peach samples were purchased and selected on the base of ripeness, shape, free from bruised surface and fungal contamination. Samples were immersed in 0.1%(V/V) trichloroacetic acid for two minutes and rinsed a couple of times with sterile distilled water. Peach samples were then divided into four groups, one is a control group while the other three were inoculated with three major post-harvest pathogenic fungi: *Moniliniafructicola*, *Rhizopus stolonifera* and *Botrytis cinereal.* PEN3 e-nose was used to collect the data. PLS-DA was used to discriminate the data. For the control group and *Rhizopus stolonifera* the accuracy was 100% while for *Botrytis cinereal* and *Moniliniafructicola* the accuracy was 86.67%. The overall accuracy achieved by this model was 90.00% (Liu *et al.,* 2018).

Peach fruits were harvested at commercial maturity. Fruit free from mechanical damage and disease was selected for freshness analysis using e-nose. Peach fruit was divided into two groups based on storage temperature. Group 1 was stored at 20 °C while group 2 was stored at 0 °C. Data was collected from group 1 from day 1 to day 13 with one-day intervals while in group 2 data was acquired 1st, 3rd, 5th, 7th, 9th, 11th, 17th, 25th, 33rd, 41st, and 49th days. Two types of e-nose were used. One is self-made, consisting of TGS813, TGS816, TGS822, TGS826, TGS2600, TGS2603, TGS 2610, TGS26011, TGS2620 and MQ137, MQ138. The other is the commercial e-nose Fox 4000. Group 1 using self-made e-nose with PLS-DA and LS-SVM models gave an overall accuracy of 88.78% and 88.77% respectively. PLS-DA and LS-SVM models in group 2 gave overall accuracy of 95.38%. Group 1 with commercial e-nose with PLS-DA and LS-SVM models gave an overall accuracy of 94.20% and 92.87% respectively. In group 2 overall accuracy of PLS-DA and LS-SVM models was 98.61% (Wei *et al.*, 2018).

Peach fruits were harvested and selected based on uniform commercial maturity with no mechanical wound or insect pest attack. The fruit was stored at 20 °C and data was acquired daily until the fruit was decayed using a Fox 4000 e-nose system. PLSR, LS-SVM, and multiple fitting regression based on gaussian fitting function (MFRG) were used to forecast the day before decay. PLSR showed a low accuracy rate of 61.18% while LS-SVM and MFRG had higher accuracy of 74.68% and 77.22% respectively (Huang *et al.*, 2017).

Yellow flesh peaches were harvested and selected on the basis of uniform size, colour, maturity. It is made sure that selected ones must be free from insect pest attack and mechanical injuries. The selected fruits were divided into three groups based on compression. Group 1 the control group, consisted of fruits without any compression damage. Group 2 included fruits that were compressed by 5mm, while Group 3 contained fruits compressed by 15mm. TA.XT Plus Texture Analysis was used to perform the compression test. Self-developed e-nose consisting of 14 sensors namely TGS813, TGS821, TGS822, TGS826, TGS2600, TGS 2602, TGS2610, TGS2611, TGS 2620, MQ2, MQ4, MQ5, MQ136 and MQ138 was used to collect data. PLSR and LS-SVM showed an overall accuracy of 74.44% and 77.88% respectively (Yang *et al.*, 2020).

Litchi: Litchi is a fruit that grows in subtropical to tropical climates and is farmed all over the world. People everywhere enjoy it for its juicy, sweet flavour and its nutritional benefits (Zhao *et al.,*2020). Litchi provides us with important nutrients such as polyphenols, polysaccharide, minerals and vitamins (Cabral *et al.*, 2014).

Guiwei litchi was harvested at 80-90% maturity and divided into three groups: injury-free, mild injury and severe injury. Mild and severe injury groups then further dropped from 80 and 100 cm height respectively. There was no apparent injury in the mildly group but cracks on the pericarp were noticed. A commercial e-nose PEN3 was used to perform sampling. Overall detection accuracy achieved was 91.43% using KNN (Xu *et al.*, 2020)

Litchi fruits were harvested and undamaged, uniform size fruits were selected. Litchi was divided into three groups. Group 1 has a room temperature environment and has 25 °C. Group 2 has refrigerator storage and the temperature was 3-5°C. Group 3 had a controlled atmosphere environment at 3-5 °C with 90-95% relative humidity and 3-6% oxygen content. At room temperature litchi was evaluated from 0-4 days while in a controlled and refrigeration environment the testing days were 0-8 with one day intervals. PEN 3 e-nose was used to collect data. Back propagation neural network was used to train the model and the test accuracy was 89.33%, 100% and 100% for room temperature, refrigeration environment and controlled atmosphere respectively (Xu *et al.*, 2016a).

Five varieties of ripe litchi namely Baili, Jidi, Xiabuli, Guiwei and Lingengnuo were used in the experiment. Fruit with uniform size and maturity were analysed via PEN3 e-nose for detecting varieties difference. PCA and LDA show a total 99.88% and

87.72% variance respectively. SVM achieved an accuracy of 92% in detecting different varieties. Probabilistic neural networks have successfully classified the different varieties with 84% success rate (Xu *et al.*, 2016b).

Strawberries: Strawberries are a member of the rose family and are cultivated worldwide. Strawberries are appreciated widely for their colour, aroma and taste. This fruit is rich in many substances such as folates, anthocyanins, carotene, vitamin C, minerals, polyphenols and has anti-inflammatory and antioxidant properties (Giampieri *et al.*, 2012).

Fresh strawberries were purchased from the market and divided into three groups. Group 1, 2 and 3 were subjected to fall on a steel plate from the height of 20, 40 and 60 cm respectively to obtain the different extent of the damage. FOX 4000 e-nose was used to collect volatile compounds released by the strawberries at 4, 8 and 24 hours. The PLS-DA model was employed and at 4, 8 and 24 hours the accuracy was 100%, 94.1% and 85.3% respectively. The overall accuracy achieved by PLS-DA was 92.1% (Cao *et al.*, 2022).

Strawberries were harvested at commercial maturity. Two hundred and sixty-four strawberries of similar size; free from mechanical damage were selected. Strawberries were divided into four groups with different duration of vibration to simulate different transport distances. Group 1 strawberries had no vibration, group 2 strawberries were placed under vibration for half hour, group 3 strawberries were placed under vibration for one hour and strawberries of group 4 were kept under vibration for 2 hours. TH-600 vibration test system was used to induce vibrations. Fox 4000 e-nose was used and signals were collected at 0 days (which was right after vibration), 1, 2 and 3 days after the vibration treatment. Overall accuracy using LS-SVM and PLSR was 90.88% and 91.66% respectively (Rao *et al.*, 2020).

Strawberries were harvested and divided into two batches free from disease or wound. One batch was tested via commercial e-nose PEN3 while the other batch was analysed by self-designed e-nose. Self-designed e-nose consists of 6 sensors namely MQ3, MQ136, MQ138, TGS2602, TGS2611 and TGS2620. PLS-DA and SVM models were trained to analyse the freshness of strawberries. Classification accuracy via self-developed e-nose was 93.6% and 96.9% while in commercial e-nose it was 92.3% and 96.2% achieved by PLS-DA and SVM respectively (Xing *et al.*, 2018).

Strawberries were picked based on their similar size and ripeness, and they were free from any damage or insect pest damage. Three types of harmful fungi were used for the experiment: Penicillium, Botrytis, and Rhizopus. The fruit was dipped for half a minute in a liquid filled with these three types of fungi spores. Volatile from the control group and the three inoculated groups were acquired using PEN3 e-nose. MLPN was used and the accuracy of the control group, *Penicillium* species, *Botrytis* species and *Rhizopus* species was 100%, 100%, 93.3% and 96.6% respectively (Zhu *et al.*, 2013).

Pomegranate: Pomegranate is regarded as a health-promoting fruit and has bioactive compounds. It positively affects the immune system, menopausal cramps, diabetes mellitus and cardiovascular system (Czieczor *et al.*, 2018).

Pomegranates were purchased based on similarity in size and shape. The E-nose that was employed consisted of MQ series sensors namely: MQ3, MQ5, MQ9, MQ131, MQ135 and MQ136. E-nose was then used to collect data from samples infected with Alternaria spp. and the control group. Sixty samples were classified as 0, 25, 50, 75 and 100 percent of Alternaria spp. BPNN showed overall 100% accuracy while linear SVM achieved 90% accuracy in the detection of Alternaria spp. (Nouri *et al.*, 2020).

Three varieties of pomegranate were procured namely Rabab-e-Neiriz, Cap-e-Ferdows and Malas-e-Saveh. The fruit selected was free from any defect or mechanical damage and had uniformity in size and shape. E-nose consisted of 6 MQ series sensors MQ3, MQ5, MQ9, MQ136, MQ137 and MQ138 were used to collect data. PCA showed 97% data variance. The LDA model obtained a classification accuracy of 95.2% with leave-one-out-cross-validation in discriminating the varieties (Sanaeifar *et al.*, 2016).

Conclusion: The use of electronic nose and machine learning in the agriculture sector has seen a significant rise in recent years. This technology offers a reduction in human errors that can occur due to illness, fatigue, or mental stress. Many studies have been conducted in the past decade to explore the potential of electronic nose and machine learning algorithms in evaluating the quality of various fruits. The increased interest in this technology can be attributed to its cost-effectiveness and fewer resource requirements compared to lab techniques such as high-performance liquid chromatography, gas chromatography-mass spectrometry, and spectrophotometer. This review has highlighted the potential of electronic nose and machine learning in fruit quality evaluation, noting the high accuracy of detection achieved. However, it also emphasises that there is still much work to be done in this area. A significant gap remains in the application of these technologies to major fruits such as citrus, banana, and mango. Therefore, further research and development are required to fully realise the potential of electronic nose and machine learning in fruit quality evaluation.

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