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Original Article

E-Nose for Cashew Apple Ripeness Detection for Autonomous Fruit Plucking

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***Abstract** - Electronic Noses are a helpful instrument in sensor technology. They are used in various industries, including food, cosmetics, agriculture, and others, for quality assurance and ripeness monitoring, process improvement, and product creation. It acts like a human nose, working as an electronic olfactory using an array sensor. Electronic Noses (E-Noses) have found several applications in agriculture due to their ability to detect and analyze odours and volatile compounds. During ripening, fruits release Volatile Organic Compounds (VOC), producing aroma. E-Nose can identify the VOC emission of fruit during its ripening stage and measure the quality of the fruit. E-Nose was developed for ripe cashew fruit detection using an array of MQ sensors in this proposed work. Their ability to analyze and differentiate aroma profiles makes them essential for ensuring the ripeness quality of cashew fruits and meeting farmer preferences. Pattern recognition of sensors was done using PCA, Random Forest, and DNN. Experimental results on various Tamil Nadu cashew varieties were more accurate in feedforward DNN analysis, and 96.85 % of the cashew fruit samples were detected precisely.*

***Keywords** - E-Nose, Cashew, MQ sensor, VOC, DNN.*

1. Introduction

E-Nose has recently been widely used in various fields, especially agriculture and food industries, for monitoring fruit ripeness, quality checking, and grade classification. E-Nose Technology provides many valuable applications to fruit industries by evaluating the aroma of the fruit during all development stages, pest controlling, detecting fruit harvesting time, fruit delivery, storage and fruit quality in the market. Its aroma, colour and texture measure fruit quality. Those features change as the fruit matures, ripens and overripens. Each and all different fruit varieties show different aroma characteristics because of the presence of volatile compounds behind their aroma.

Substituting humans and their noses, E-Nose comes into the big picture for identifying fruit maturity stages, providing harvesting suggestions, and grading [13]. Apart from cashew nut, the major product of cashew cultivation, cashew nut shell liquid and cashew apples are the two main products of the tree that are processed and used by various industries like food processing, Paint, cosmetics, and pharmaceutical industries worldwide. Cashew fruit, which is edible, initially looks greenish yellow and gradually becomes more prominent in size with more yellow or red colour. As the fruit matures, it involves changes in its taste and texture, and the apple becomes more sweeter and more nutritious. Later, when they reach full maturity, cashew apples will lose their nutritional content due to the deterioration of the apple. Apples must be harvested from the orchards at the right time to get the nutritional benefits of cashew fruit. Cashew fruit was typically gathered by picking up fallen fruits after they had fully ripened, which was a dangerous practice.

Dried leaves can repress cashew nuts; therefore, manual harvesting results in leaving it in the field itself. To improve crop cultivation and yield, an autonomous system for cashew fruit harvesting must be built with AI and IOT technologies. E-Nose can discriminate cashew fruit between Ripe and Unripe. The accuracy of the classification by E-Nose depends on the sensors used, VOC present and statistical classification technique used.

The maturity of the cashew apple involves several stages: flowering, fruit development, immature, mature, harvest, and postharvest. The chemical composition of cashew apples differs during these stages due to various factors, mainly plant genetics and environmental factors. Cashews are rich in Volatile Organic Compounds, namely Methylbutanoate, Methyl-2 butanoate, Methyl 3-methyl pentanoate, 3-carane, Methyl (E)-2-methyl-2-butanoate, ethyl 4-methyl pentanoate, 2-hexenal, Butyl 3-methyl butanoate, Butyl pentanoate, 3-methyl butanoic acid behind its aroma or flavour. [12] Esters were the dominant chemical class regarding the number of compounds and the chromatographic peak area, accounting for 48 detected compounds.

The essential compounds like Methyl butanoate, Methyl 3-methyl butanoate, Ethyl 2-methyl butanoate, Methyl 2-butenoate, Methyl 3-methyl pentanoate, 3-carene, Methyl (E)-2-methyl-2-butenoate, Ethyl 4-methylpentanoate, 2-hexenal, Butyl 3-methylbutanoate, Butyl pentanoate, and 3-methyl butanoic acid were found to be essential for the fruit aroma differences in different varieties and flavour of cashew fruit.

2. Literature Review

Developing an Electronic Nose (E-Nose) for cashew fruit or any specific application typically involves selecting suitable sensors to detect and identify specific odours or volatile compounds. Cashew fruit has a unique aroma, and to create an effective E-Nose for it, sensors that are sensitive to the compounds responsible for its odour are required. The following describes some types of sensors that may be suitable for developing an E-Nose for cashew fruit:

1. Metal Oxide Gas Sensors (MOX): MOX sensors are versatile and widely used in E-Nose applications. They can detect a range of Volatile Organic Compounds (VOCs) and are suitable for detecting the characteristic odours of fruits like cashews.
2. Conductive Polymer Sensors: These sensors are sensitive to changes in electrical conductivity when exposed to different odours. They are often used in E-Noses to detect a wide range of volatile compounds.
3. Quartz Crystal Microbalance (QCM) Sensors: QCM sensors are sensitive to mass changes on the sensor surface caused by the adsorption of volatile compounds. They can detect specific odours, including those from cashew fruit.
4. Surface Acoustic Wave (SAW) Sensors: SAW sensors are susceptible and can detect changes in surface acoustic waves caused by interactions with volatile compounds. They are suitable for discriminating between different odours.
5. Optical Sensors: Optical sensors, such as colourimetric and fluorescent sensors, can be designed to respond to specific volatile compounds in cashew fruit aroma. They offer high sensitivity and selectivity.
6. Electrochemical Sensors: Electrochemical sensors, like amperometric or potentiometric sensors, can be tailored to detect specific gases or volatile compounds. They are commonly used in E-Nose applications.
7. Selective Sensors: Depending on the specific compounds, cashew fruit can be detected, and sensors that are selective to those compounds must be identified. For example, if aimed to focus on seeing esters responsible for the fruit’s aroma, ester-selective sensors can be chosen.

It is essential to consider the specific volatile compounds in cashew fruit aroma and choose sensors that can detect those compounds effectively. Volatile Organic Compounds (VOCs) in cashew fruit are responsible for their unique aroma and flavour. The specific VOCs in cashew fruit can vary depending on the fruit’s ripeness and variety. Some of the common VOCs found in cashew fruit include:

1. Anacardic Acid: Anacardic acid is crucial in cashew nut shell oil and the apple’s skin. It contributes to the characteristic astringency and flavour of cashew fruit.
2. Cardol: Cardol is another cashew nut shell oil compound. It can contribute to the fruity and nutty aroma of cashew fruit.
3. Anacardic Aldehyde: Anacardic aldehyde is an aromatic compound that contributes to cashew fruit’s overall aroma and flavour.
4. Limonene: Limonene is a common terpene found in many fruits, including cashews. It contributes to the citrusy and sweet aroma of cashew fruit.
5. Furfural: Furfural is a volatile compound that can contribute to the caramel-like notes in cashew fruit aroma.
6. Ethyl Decanoate: Ethyl decanoate is an ester that contributes to the fruity aroma of cashew fruit.
7. 2-Methylbutyl Acetate: This compound is responsible for the banana-like aroma sometimes detected in cashew fruit.

Tamil Nadu, India, is known for its cashew cultivation, and the state produces several cashew varieties, each with its unique aroma profile. Tamil Nadu cashew varieties and their typical aroma characteristics are:

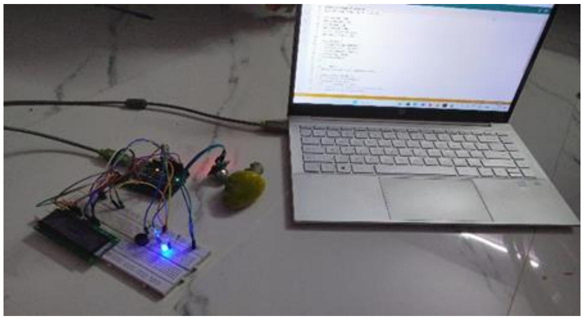
1. Mundakanni: Mundakanni is a popular cashew variety in Tamil Nadu. It is known for its distinct aroma, fruity, and nutty notes. The aroma is often sweet and pleasant, with hints of tropical fruits like mango and a mild nuttiness.
2. Bappakkai: Bappakkai cashews are another variety from Tamil Nadu. They are known for their aromatic quality, often described as having a robust and fruity aroma with a hint of nuttiness.
3. W210 and W240 are cashew grades commonly produced in Tamil Nadu. They are known for their large size and balanced aroma profile, including fruity, nutty, and mild floral notes.
4. W320: W320 cashews are another popular grade produced in Tamil Nadu. They are known for their medium size and well-rounded aroma that combines fruity, nutty, and floral notes.
5. W450: W450 cashews are smaller than some other grades but are still highly regarded for their aroma. They typically have a slightly more robust, nutty aroma with sweet and fruity undertones.

Table 1. Comparison studies with E-Nose system available for fruit classification

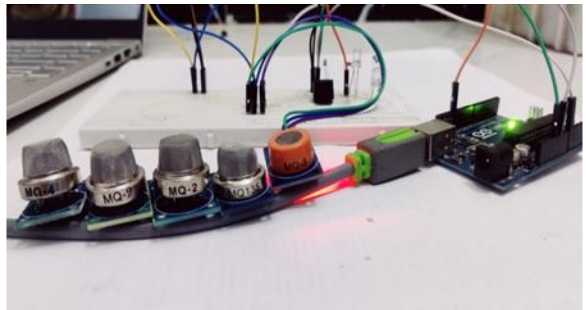
Category	Samples	Sensor Used	Data Analysis	Application	Accuracy
Banana [11]	15 Bananas of the Same Size	MQ3,5,9,131,135,136	PCA, LDA, SIMCA and SVM (Better)	Ripeness Detection	98.66 %
Banana, Cocktail Tomatoes, and a Yellow Pepper [15]	Not Available	TGS 2620 VOC Sensor	-	Freshness Detection	-
Apple, banana, Orange, Grapes, Pomegranate [1]	24,000	MQ5, MQ4, TGS 2620, TGS 2610, TGS 2602, DHT 11	ANN	Ripeness Detection	>= 95%
Apple (Moldy) [3]	1832	PEN3	BPNN	Moldy Apple Detection	96.3% and 90.0% (Group A), 77.7% and 72.0% (Group B)
Berries [4]	120	MQ3, TGS2602, MQ9, TGS2611, TGS2610	ANN, PCA, LDA	Ripeness Detection	ANN: Blackberry – 100% and Whiteberry – 88.3% PCA – Blackberry - 97% and 93% Whiteberry LDA – Least Correction Classification - Blackberry- 96.67% and Whiteberry – 85%
Cantaloupe [14]	-	MQ3	Fuzzy Logic	Ripeness Detection	-
Mango [5]	-	MQ Sensors	Fuzzy Logic	Ripeness Detection	Unripe - 93.33 Ripe- 86.67
Banana [6]	35 Plants	MQ2, MQ3, MQ4, MQ5, MQ135	ANN	Fusarium Wilt Disease Detection	-
Dragon Fruit, Snow Pear, Kiwi Fruit, and Fuji Apple [8]	-	MQ3,4,6,7,8,135,136,138	PCA	Freshness Detection	93.24%, 91.12%, 93.16%, 93.69% Respective to the Fruits Mentioned
Lemon, Banana, Grape [16]	2500	MQ2, MQ 135, MQ3, TGS2610, TGS 2611	Feed Forward Stochastic Gradient Descent	Classification	99%

The primary aim of cashew cultivation is cashew nut, but the apples are wasted in large numbers in the field without consideration. However, the cashew apples can be utilized for alcoholic production using the fermented juice[17].

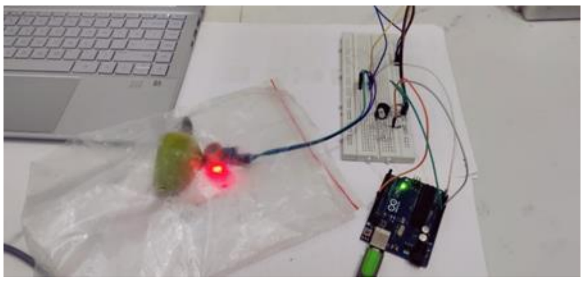
According to B. Bicalho [19], alcoholic Volatile Organic Compounds present in cashew apples are 1-Octanol, Hexadecanol, and Octadecanol with 1072, 1880, and 2084 retention indices obtained by headspace extraction. Benady et al. developed a sensing device in 1995 with a single semiconductor gas sensor housed in a small cup and placed on the surface of fruits of three different muskmelon cultivars. This work demonstrated the first interest in using electronic noses as a non-destructive method to study the characteristics of fruits.



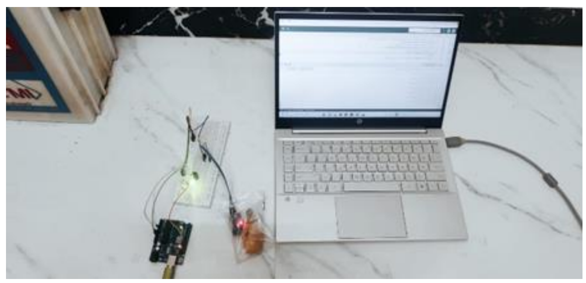
(a) Prototype model



(b) Different MQ series used for the proposed work



(c) Unripe cashew detection



(d) Ripe cashew detection with the greenlight alert

(e) Adding array of sensors E-Nose creation for cashew detection

(f) Sensor value detected by MQ sensor

Fig. 1 Hardware setup of the proposed system and the sensor value of the E-Nose

The device could accurately sort fruits into three ripeness groups (unripe, half-ripe, and completely ripe) and distinguish between ripe and unripe fruits with a discrimination accuracy of 90.2%.

The same research team examined blueberries to assess ripening stage and fruit quality [18] and identify the variation in E-Nose response among blueberry cultivars (the same year). Gordan et al. in 2012 [7] identified that phenolic compounds decreased as the fruit ripens, whereas the ascorbic acid and antioxidant capacity increased during the ripening stage. The significant flavonoids of cashew matured fruit are myricetin 3-O-rhamnoside, quercetin 3-O-galactoside and quercetin 3-O-rhamnoside.

In the study, it was noted that many E-Nose types like PEN2, PEN3, FOX 4000, Cyranose 320, Libra Nose, EOS 835, Aromascan, E-Nose 4000, enQbe were proposed by many researchers for fruit aroma characterizations [2]. The aroma of cashew fruit can be pretty complex, and individual preferences may vary. The exact aroma profile can also vary among different cashew fruit varieties. To develop a more precise understanding of the aroma of a specific cashew fruit variety, sensory evaluations need to be carried out or using analytical techniques such as gas Chromatography-Mass Spectrometry (GC-MS) to identify and quantify the particular volatile compounds responsible for its aroma.

3. Materials and Methods

3.1. Sample

The study used cashew apple samples with nuts collected from orchards of Cuddalore districts, specifically from KumalanKulam, Kurincipadi, and Silambinathanpettai village farms. Red and yellow cashew samples of different varieties were tested for their aroma. Also, the sample collection includes ripe and unripe cashews packed in a zip lock cover.

3.2. E-Nose for Cashew

An E-Nose system was proposed for cashew ripe fruit identification that was missed by the imaging system due to occlusions using an array of gas sensors used to detect the VOC. The cashew under detection was kept in a separate sample chamber, and the sensor array was placed in a different sensor chamber. The array consists of 5 sensors, MQ2, MQ3, MQ4, MQ9, MQ135 shown in Figure 1(b). The used sensors's detection range is shown in Table 2. As in Figures 1(c) and 1(d), both Ripe and Unripe cashews are exposed to a sensor array to detect ripeness.

The hardware setup of the proposed E-Nose system includes Arduino Uno, buzzer, display board, green and blue light, MOS sensors in the array shown in Figure 1(e) and Figure 1(a) shows the entire hardware setup of the E-Nose. Arduino Uno provides a 5V power supply to the sensor array for inputting and heating the sensor.

The E-Nose proposed produces an analog sensor value, which is the ripeness range of the fruit on experimentation, as in Figure 1(f). Based on the detected Parts Per Million (ppm) range, the result shows whether ripe cashews were seen. It was observed that the ripe cashew ppm ranges from 1000 to 2000. Depending on the concentrations, LED lights are turned on.

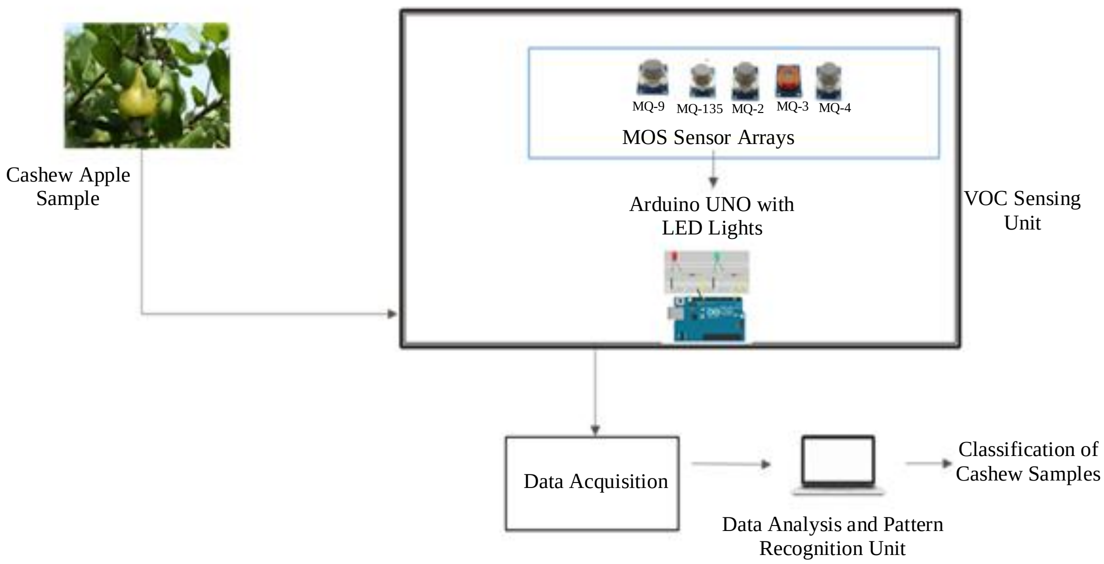


Fig. 2 System architecture of the proposed work

Table 2. Sensors used in E-Nose system for cashew

Sensor	**Gases Identified**	**ppm Range of Detection**
MQ2	Methane, Butane, LPG, Smoke	200-10000
MQ3	Alcohol, Ethanol, Smoke	25 -500
MQ4	Methane, CNG Gas	300-10000
MQ9	Carbon Monoxide, Flammable Gases	10-1000 CO, 100-10000 Combustible Gas
MQ135	Air Quality (CO, Ammonia, Benzene, Alcohol, Smoke)	10-1000

3.3. Data Analysis

The array of MOS sensors was made to expose the VOCs from packed cashew samples. The sensors' response values were collected for analysis. A total of 5870 sample sensor data values were recorded in a file. Multivariate statistical analysis can be applied to the sensor data using techniques like PCA, LDA, ANN, CA, PLS, MLR, and fuzzy logic [9, 10].

In this proposed work, the dataset file was inputted to PCA, Randon Forest and standard feedforward Deep Neural Networks (DNNs) for analyzing the E-Nose working. The overall system architecture of the proposed system is shown in Figure 2.

4. Results and Discussion

Several experiments were conducted under various conditions to identify the optimum experimental conditions. The response of the E-Nose was recorded and analyzed for its performance by feedforward DNNs. The accuracy shows 96.85 with a loss of 0.1752. The confusion matrix of DNN with an accuracy of 96.85% is shown in Figure 3.

The graph generated using the sensor dataset, which represents the feature importance classified using the Random Forest classifier, is shown in Figure 4. The variance ratio of principal component analysis is given in Figure 5.

In Table 3, the comparison of various baseline models with the proposed feedforward DNN model was given.

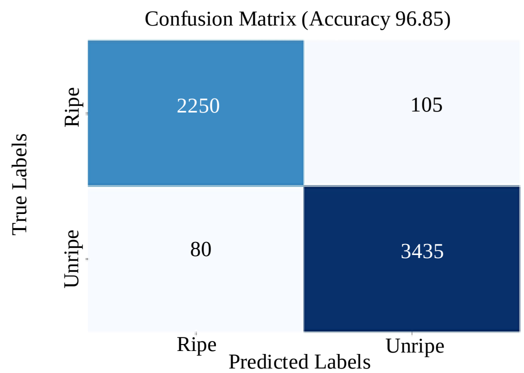


Fig. 3 Confusion matrix of feedforward DNN

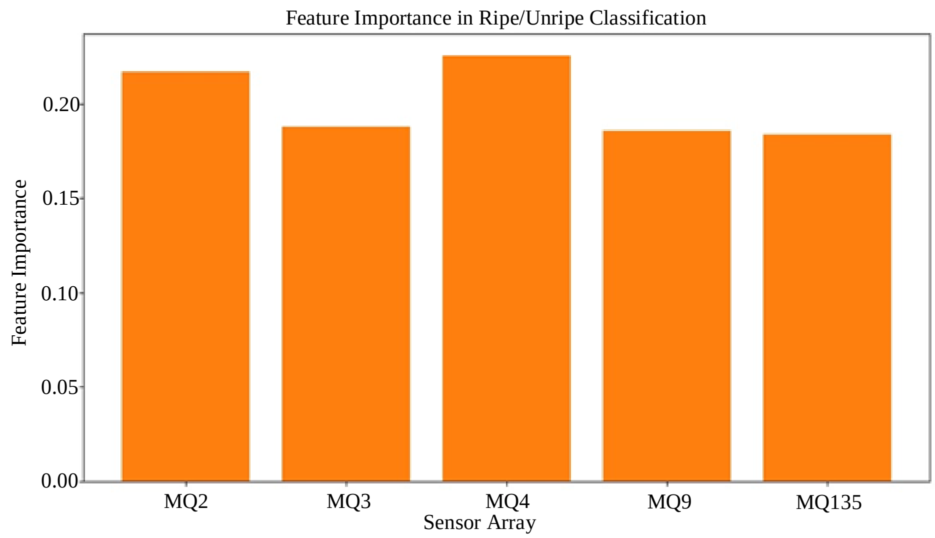


Fig. 4 Feature importance in classification by MQ2, MQ3, MQ4, MQ9, MQ135 sensors using random forest classifier

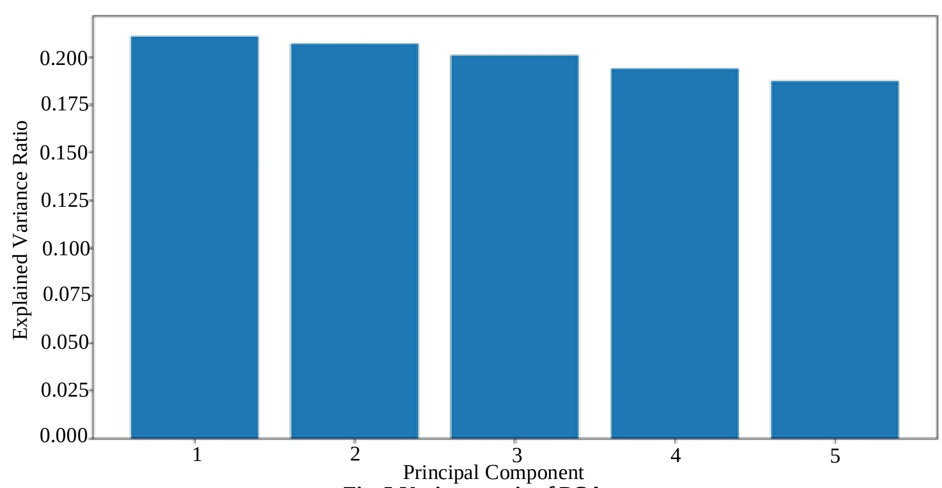


Fig. 5 Variance ratio of PCA

Table 3. Performance metrics of enhanced feedforward DNN model with other baseline models

Models/ Metrics	Random Forest	PCA	RBFNN	Proposed Feedforward DNN
Accuracy	93	95.86	96.3	96.85
Precision	87.6	95.32	95.91	96.56
Recall	88.63	94.01	95.23	95.54
F1_Score	88.13	94.12	95.39	96.05

5. Conclusion

In conclusion, the proposed system, which is an integration of an Electronic Nose (E-Nose) equipped with Metal Oxide Semiconductor (MOS) sensors for cashew ripe detection, coupled with advanced data analysis techniques such as Principal Component Analysis (PCA), Random Forest, and standard feedforward neural network, offers a promising and comprehensive approach for quality assessment in the cashew industry.

The standard feedforward neural network is the most effective method among the analysis techniques applied in this study. Its ability to capture intricate patterns and relationships within the sensor data allows for highly accurate and reliable cashew ripe detection. This neural network model leverages the full potential of the E-Nose by adapting to the complex and dynamic nature of cashew ripeness, making it well-suited for real-world applications. While PCA and Random Forest also contribute valuable insights and discrimination capabilities, they may fall short in handling the subtleties and nuances of cashew ripeness due to their inherent limitations. PCA primarily focuses on dimensionality reduction and visualization but may not capture complex non-linear relationships in the data.

Random Forest, while robust, may not be as adaptable to the changing conditions and variations in cashew samples as the neural network. The neural network's ability to continuously learn and improve its performance with more data makes it a promising solution for long-term cashew ripeness detection needs. Its adaptability, precision, and capacity to handle evolving datasets make it the preferred choice for accurate and efficient quality control in the cashew industry.

In summary, the combination of an E-Nose equipped with MOS sensors and the utilization of advanced data analysis techniques, with the neural network as the centrepiece, represents a compelling solution for cashew ripe detection. This approach holds great promise for enhancing the efficiency and reliability of cashew processing and quality control while minimizing waste and ensuring consistent product quality. Furthermore, this work can be used to optimise sensors for cashew fruit identification.

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