

## Development of Electronic Nose for early spoilage detection of potato and onion during post-harvest storage

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Article

**ABSTRACT** Every year, roughly around one-third of the horticultural commodities worldwide are lost in post-harvest stages due to various abiotic stresses like temperature, humidity and water, and biotic stresses like pathogens, insects and pests. This calls for the need for continuous monitoring of the health of stored fruits and vegetables for early detection of spoilage of



these perishable and semi-perishable items. For all practical purposes, regular manual physical inspection of the storage area is not a feasible solution. Vegetable ageing, spoilage and infection are associated with the emission of volatile organic compounds (VOCs), often with a foul odour. GC-MS based chemical analysis shows that vegetable effused VOCs during storage vary significantly, and the concentration of VOCs increases with more degree of spoilage. Regular chemical analysis is not a feasible solution because of the high cost and lead time of such a process. A probable alternative solution is rapid, low-cost, in-situ and online testing employing electronic nose (e-Nose). This study attempts a novel method for early detection of spoilage of stored potato and onion employing an e-Nose, named e-POT, designed and developed for the purpose. The study shows encouraging results and may further be exploited for making it suitable for commercial applications.

**Keywords:** Electronic Nose (e-Nose), Volatile Organic Compound (VOC), Metal Oxide Semiconductor (MOS), Principal Component Analysis (PCA), Probabilistic Neural Network (PNN), Partial Least Square (PLS)

### INTRODUCTION

India is predominantly an agrarian economy, and the contribution of the agricultural sector towards GDP<sup>1,2</sup> in 2020-21

is 20.20% and has an increasing trend as compared to 18.40% and 17.60% in 2019-20 and 2018-19 respectively. India is the second-largest producer of fruits and vegetable worldwide<sup>3</sup> and has the potential to become a self-sufficient food producer as well as a major food exporter. About 30-40% of these fruits and vegetables simply go to waste, creating a huge annual loss. However, the increasing demand due to population growth and many other factors had forced India to rank 101 in Global Hunger Index (GHI) with a score of 27.5, which is regarded as serious. One of the major reasons behind this is the enormous postharvest loss of agricultural commodities due to various issues. The main factors affecting this loss are insufficient and

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improper storage infrastructure, growth of microorganisms in favourable hot and humid Indian conditions, insect and pest attacks, etc. Instead of focusing only on agriculture productivity enhancement, a holistic approach to target minimizing postharvest losses would definitely yield higher returns. This would also help India in poverty alleviation and improvement in general health, nourishment and food security for its people.<sup>4</sup>

The biggest contributors to waste are the lack of adequate high-quality storage and cold storage facilities, and the most susceptible food categories are the perishable and semi-perishable fruits and vegetables. India is having a serious shortage of warehouses for food grains also, but we limit our discussion here to fruits and vegetables only. Recently, an increase in cold storage facilities has been observed in the country through a couple of financial assistance schemes by the Government. The number of cold storages is still inadequate, with a shortfall of 126 lakh tonnes compared to the requirement as per the projection of the National Centre for Cold Chain Development (NCCD).<sup>5</sup> This creates a hindrance of tapping the potential of increasing the production of fruits and vegetables. Another problem associated with the infrastructure is the uneven or skewed distribution of cold storage across the country. The majority of these facilities are located in Uttar Pradesh, Gujarat, Punjab, Telangana, Rajasthan, Haryana and Orisha. However, states like Maharashtra and Karnataka, with a large amount of exportable produce, do not have adequate cold storage capacity. Bihar, Chhattisgarh and West Bengal are the lowest in order in terms of cold storage as per horticulture produce<sup>5</sup>. Depending on the storage requirement, the temperature is maintained at 8-10 °C or 15 °C. In some cases; vegetables are also stored at room temperature for a shorter period. The optimum relative humidity (RH) required for the storage of potato is 90-95%, whereas 65-75% is for onion. Unsuitable storage conditions coupled with microorganism infection destroy the nutritional values of the crops and make them unsuitable for human consumption. Hence proper monitoring and control of temperature and RH in the storage chamber is also of utmost importance.

Ageing and decomposition or spoilage is a natural phenomenon and occurs in the case of all fruits and vegetables in their life cycles. A proper storage system may only enhance the life of the stored vegetables and can only delay the time of spoilage or, in other words, enhance the shelf life. Emission of VOCs take place in plants throughout their lifetime, and fruits and vegetables continue to release VOCs in a greater capacity even during postharvest storage due to various biotic and abiotic stresses. Many of these VOCs have been identified as biomarkers for different biotic and abiotic stress conditions of many fruits and vegetables. Detection of these VOCs, qualitatively and quantitatively, may be indicative of the health of the stored commodities and may lead to early corrective intervention, thereby saving huge economic loss.

The environment in a controlled storage chamber also poses a negative impact on the stored vegetables in the form of abiotic stresses like low temperature, high RH, low oxygen and high CO<sub>2</sub> concentration. A few symptoms of chilling injury are browning on the surface and internal sides, pits on the surface, increase in

softness, unwanted flavour generation, etc. High RH in the chamber causes the stored crops to absorb water resulting in loss of flavour, sweetness, texture, juiciness, etc. Respiration of stored crops decreases O<sub>2</sub> and increases CO<sub>2</sub> concentration inside the container. A low level of O<sub>2</sub> induces injury to crops. A high level of CO<sub>2</sub> enhances shelf life but increases susceptibility to diseases. The mechanical damage that occurred during postharvest handling, transportation and storage account for early ripening and cell membrane degradation of crops under storage.<sup>6</sup>

Biotic stress on the stored crops is the damage done by bacteria, fungi, insects and other living organisms. They result in a change in colour and deterioration of compounds and also lead to the emission of certain VOCs. These microbial VOCs can be classified under alcohols, ketones, benzenoids, sulphides, alkenes, pyrazines, and terpenes. Bacteria and fungi can infect crops and may account for a great loss in storage. Bacteria infect mostly the internal sites, whereas fungi infect externally as well as internally depending upon crop type and fungal strains. Chances of insect and pest infestation in stored vegetables are very less, but in rare cases, traces of larvae or eggs can be found. On the other hand, abiotic agent-induced VOCs are linked to aromatic alcohols and acetate groups. A comprehensive list of VOCs due to biotic and abiotic stress on stored vegetables can be found in the Subway plot by S. Tiwari et al.<sup>6</sup> All these VOCs can very well act as biomarkers for the detection of the spoilage causing agents and monitoring the health of the horticultural commodities during storage.

Although a correlation between spoilage of vegetables due to biotic-abiotic stresses with emanated VOC had already been established in earlier studies, tangible methods for online in-situ detection of VOCs are yet to be developed. The prevailing conventional method is a laboratory-based analysis of headspace samples employing sophisticated analytical instruments, as described in the following paragraph.

Flame Ionization Detection (FID)<sup>7</sup> is a universal detector for organic compounds, operates by ionizing within a burning hydrogen flame in two stages, allowing for the measurement of hydrocarbon concentrations in VOCs. This method enables detection in the range ~ 0.05 ppm for most VOCs and ~ 2 ppm for benzene. The method can be used for hot and wet samples. It only responds to carbon atoms, and the sample cannot be re-used. The detection limit of Infrared (IR) Absorption Spectroscopy<sup>8</sup> varies between 0.3 to 9.2 ppm for non-methane VOCs. The method requires minimal sample preparation with no sample destruction but requires expensive optical components. Photo Ionization Detectors (PID)<sup>9</sup> are capable of detecting less than 0.1 ppm for most VOCs. They are compact, accurate, affordable, and reliable real-time VOC monitoring devices with non-destructive sample analysis. Disadvantages are they cannot detect methane and are affected by humidity. Gas Chromatography-Mass Spectrometry (GC-MS)<sup>10</sup> ionizes VOCs in the presence of a magnetic field and ion beam while passing through a gas mobile phase, allowing multiple VOC components with an ultra-low limit of detection (0.5 ppb). Proton Transfer Reaction Mass Spectrometry (PTR-MS)<sup>11</sup> involves chemical ionization and drift tube technologies used for real-time measurements in the

laboratory. The method can detect ultra-trace level detection in the range of 10 -100 ppt. This method is insensitive to water molecules, but different isomers of the same compound cannot be separated. Fourier Transform Infrared (FTIR) Spectroscopy<sup>12</sup> measures the amount of light absorbed by a sample at each wavelength allows the component detection in VOCs at the level of 2 ppb. This method cannot detect compounds outside of the library of spectra accurately, and H<sub>2</sub>O and CO<sub>2</sub> spectra can interfere with measurements.

Conventional laboratory techniques can provide an in-depth analysis of compound VOC samples but are not appropriate for online and in-situ monitoring of VOCs due to their bulky size, heavy weight, special carrier gases requirement and high maintenance cost.

Electronic nose (e-Nose)<sup>13</sup> has been gaining popularity and wide acceptance in different fields, agriculture and the food industry in particular. Quality assaying of food products and beverages is one of the major application domains where e-Nose has been tried for rapid sensory evaluation of quality. Application domains include tea,<sup>14,15</sup> coffee,<sup>16</sup> dairy products,<sup>17</sup> meat,<sup>18</sup> wine,<sup>19</sup> oil,<sup>20</sup> vinegar,<sup>21</sup> cocoa beans,<sup>22</sup> jasmine and concrete,<sup>23</sup> etc. Disease detection and health monitoring is another application domain in which researchers tried e-Nose for detection of asthma,<sup>24</sup> viral infections,<sup>25</sup> cancer,<sup>26</sup> tuberculosis,<sup>27</sup> cystic fibrosis<sup>28</sup> and astronaut health in space.<sup>29</sup>

Compared to human sensory evaluation of food quality, e-Nose evaluation is fast, accurate and repetitive and is free from human biases, subjectivity and error. E-Noses are not as accurate as Analytical Measurement Instruments, e.g., GC-MS and cannot measure the concentration of the constituent chemical compounds present in the sample. However, once e-Nose is trained with a good number of labelled data and a suitable machine learning model, it can predict the quality of the sample under test in different predefined classes with reasonable accuracy. The working principle of e-Nose is very different from other sensor-based measurement instruments as the odour sensors presently available are selective to all the VOCs belonging to a particular class or group of chemical compounds. The same sensor also shows cross sensitivities to a certain amount of VOCs belonging to other groups. Hence, it is literally impossible to accurately quantify the concentrations of the individual constituent VOCs in a sample. To overcome this limitation, an e-Nose is constituted with a number of gas sensors sensitive to different groups of VOCs to form a sensor array. For each training sample, the sensor array senses and creates a unique "odour print" and stores it into the memory of the device. After achieving sufficient numbers of training data covering all the quality classes, when an unknown sample is given, the device tries to find out the closest match of the obtained "odour print" from the training classes employing an artificial intelligence technique.

Owing to the concerns mentioned above, the objective of this study has been focused on developing a simple, cost-effective and field-deployable e-Nose device for early identification and quantification of the spoilage level of stored vegetables (potato and onion) through the capture of VOCs generated by these

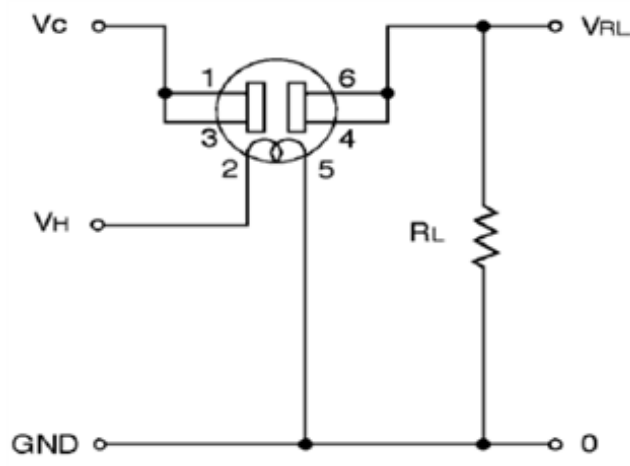
commodities under abiotic and biotic stresses in a storage environment. The selection of an appropriate set of gas sensors to form the e-Nose sensor array and to develop suitable AI-ML models are also important scopes of the study.

The study is undertaken in two phases. In the first phase, we have trials of the developed e-POT device in the 500-litre cold storage chamber stored with potato and onion, separately, one by one. The objective of this study is to check the efficacy of the e-Nose system, the selected sensors and the odour handling system in capturing and detecting VOCs. The sensor data thus captured is also analyzed to verify whether that would be able to differentiate between fresh and stale commodities with a distinct borderline between them for each commodity. In the second phase, the study is conducted in the 19000-litre capacity cold storage chamber with potato and onion. We have taken two analysis approaches here; first, we applied various classification algorithms on the captured VOC data to find out whether these models can segregate fresh and stale samples accurately. Secondly, we have applied a prediction algorithm to roughly estimate the VOC concentration, thereby predicting the degree of staleness of the stored commodity in three discrete classes.

## MATERIALS AND METHODS

### SENSOR SELECTION FOR DEVELOPMENT OF E-NOSE

Selection of proper sensors for the application is an extremely important activity, which is carried out in two stages, first by exposing a few synthetic chemicals related to spoilage of potato and onion, and then by validating the shortlisted sensors through the exposure of VOCs from real potato and onion samples, both fresh and spoilt states. We have limited our scope to Metal oxide semiconductor (MOS) gas sensors only as this is the only commercially available accurate and reliable sensors with repetitive results. As the e-POT device developed under this project supports eight sensors, a total number of eight sensors suitable for potato and onion spoilage detection are required to be found. An existing C-DAC developed portable e-Nose that operates in batch mode had been employed for sensor selection.



**Figure 1.** Circuit Schematic of a MOS sensor.

Figure 1 shows the circuit schematic of a typical MOS sensor. The sensor response of such a circuit can be defined as:

$$V_{RL} = V_C \left( \frac{R_L}{R_S + R_L} \right)$$

where,

$V_{RL}$ :	Sensor response in voltage
$V_C$ :	Circuit voltage
$V_H$ :	Heater voltage
$R_L$ :	Load resistance
$R_S$ :	Sensor resistance

The sensitivity of a MOS sensor is a normalized entity, which is defined as the difference in response of sensor in target gas and in reference gas (usually air) divided by the response in reference gas.

In order to find out potato specific sensors, first, the sensors in groups are exposed to Butyl Hexanoate, a chemical that may be found in abundance when the potato is infected with *Erwinia carotowora*. To check the sensitivities of the sensors, 30 ml of 6 ppm vapour is exposed to the sensor array, and the responses are recorded. The sensitivities of the major sensors under this test are shown in Figure 2. The priority ranking of sensors for potato spoilage determination, as is clear from Figure 2, are ordered as TGS 825, TGS 2602, TGS 2620, TGS 2611, TGS 816, TGS 823, TGS 2600, TGS 2610, TGS 832, TGS 813, TGS 821 and TGS 830.

To find sensors responsive to onion spoilage, the sensors in groups are exposed to Phenol and Hexylmethylamine, major chemicals effused on infection of the onion by *Erwinia carotowora*. To check the sensitivities of the sensors, 30 ml of 6 ppm vapour is exposed to the sensor array one by one, and the responses are recorded. The sensitivities of the sensors on exposure to Phenol and Hexylmethylamine are shown in Figure 3 and Figure 4, respectively.

Combining the responses of these two chemicals, the priority ranking of sensors for onion spoilage detection are ordered as TGS 816, TGS 826, TGS 813, TGS 2610, TGS 2611, TGS 2602, TGS 825, TGS 832, TGS 821, TGS 2600, TGS 830, TGS 823 and TGS 2620.

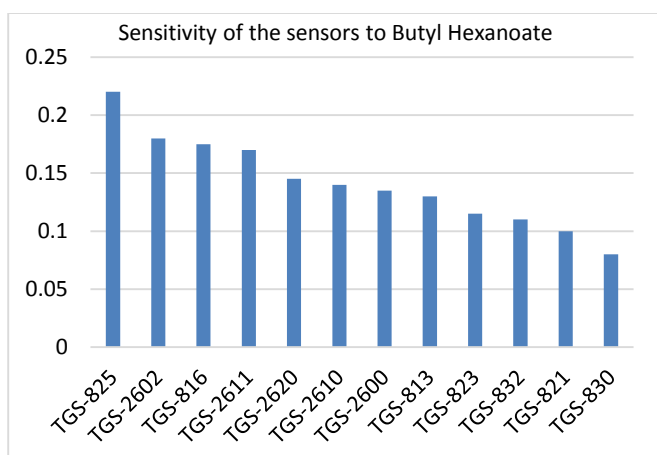


Figure 2. Sensitivity of the sensors exposed to Butyl Hexanoate.

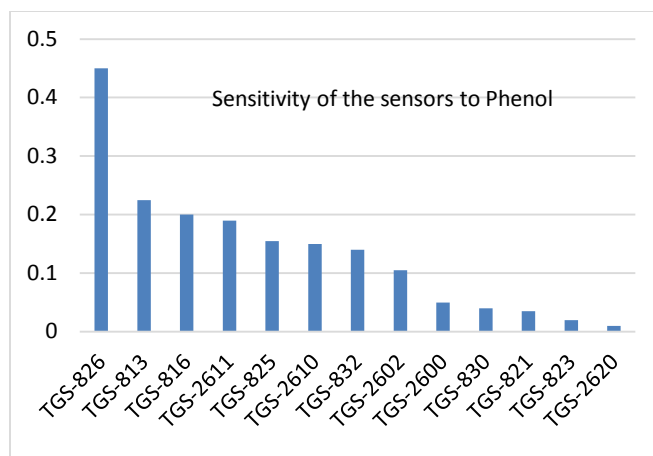


Figure 3. Sensitivity of the sensors exposed to Phenol.

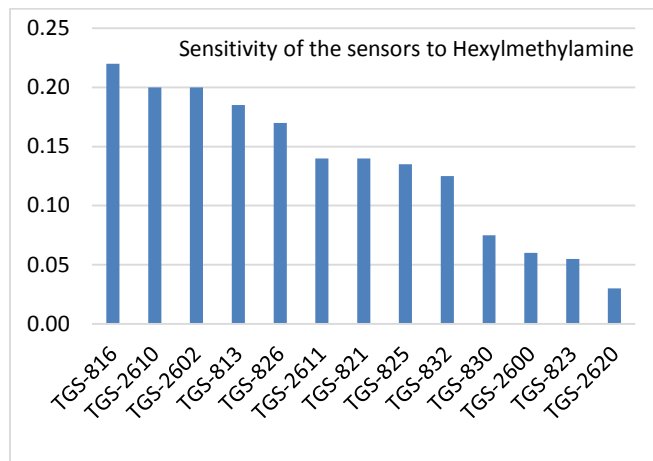


Figure 4. Sensitivity of the sensors exposed to Hexylmethylamine.

These two lists give a first-hand impression of sensors suitable for potato and onion, respectively. However, this has been observed from the figures that the first eight-nine sensors in the ranks differ very little in terms of sensitivities. Secondly, the bacteria and the chemicals considered in the above study are not the sole microorganisms or the chemicals, and there may be enormous numbers of chemicals that originated from potato and onion during spoilage because of several biotic and abiotic stress on them. Therefore, it is extremely necessary to validate these shortlisted sensors by exposing them to real potato and onion samples, both fresh and spoilt. This sensor validation study is performed in the same portable e-Nose device with 20 gm samples taken in each case. The peak responses for fresh and spoilt vegetables with differences are shown for potato and onion in Table 1 and Table 2, respectively. Figure 5 and Figure 6 show the same in the form of bar charts.

The sensor selection procedure is summarized as (i) First; the sensors are shortlisted on the basis of their sensitivity to chemicals emanated from potato and onion when they are infected with the most common microorganism called *Erwinia carotowora*. (ii) Then, they are exposed to VOCs from fresh and rotten potatoes and onions to see the differences in sensor responses. (iii) The top-ranked five sensors for both potato and

**Table 1:** Sensor responses for Fresh and Spoilt potatoes

Sensor Name	Sensor Response (in Volt)		Difference (in Volt)
	Fresh Potato	Spoilt Potato	
TGS-823	0.14	3.72	3.58
TGS-825	0.09	3.38	3.29
TGS-2611	0.25	2.42	2.17
TGS-816	0.39	1.75	1.36
TGS-832	0.68	1.86	1.19
TGS-2600	0.15	0.78	0.63
TGS-813	0.31	0.90	0.59
TGS-2610	0.42	0.97	0.55
TGS-821	0.75	1.23	0.48
TGS-830	0.30	0.68	0.38
TGS-822	0.16	0.48	0.32
TGS-2620	0.16	0.36	0.20
TGS-826	0.89	1.08	0.19
TGS-2602	2.29	0.69	-1.60

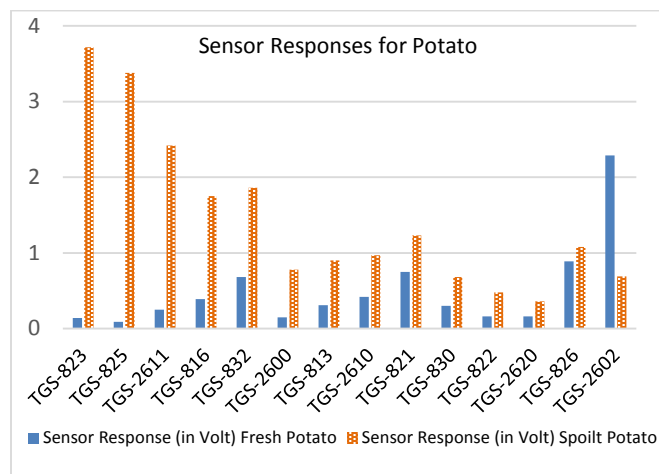
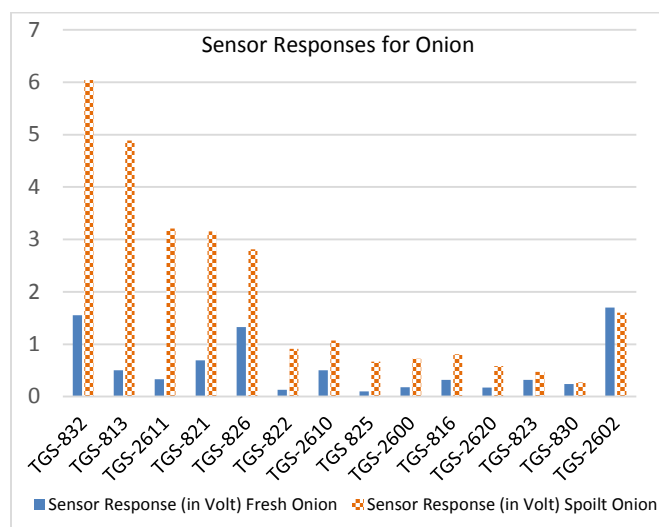
**Table 2:** Sensor responses for Fresh and Spoilt onions

Sensor Name	Sensor Response (in Volt)		Difference (in Volt)
	Fresh Onion	Spoilt Onion	
TGS-832	1.55	6.04	4.50
TGS-813	0.50	4.89	4.38
TGS-2611	0.33	3.21	2.89
TGS-821	0.69	3.15	2.46
TGS-826	1.33	2.81	1.48
TGS-822	0.13	0.91	0.78
TGS-2610	0.50	1.07	0.57
TGS 825	0.10	0.67	0.56
TGS-2600	0.18	0.72	0.54
TGS-816	0.32	0.81	0.49
TGS-2620	0.17	0.58	0.40
TGS-823	0.32	0.47	0.15
TGS-830	0.24	0.27	0.03
TGS-2602	1.70	1.60	-0.10

onion are further shortlisted. (iv) These two lists give us the final set of eight sensors as two of them are found common both in potato and onion.

From Table 1, the best responsive five sensors for potatoes are taken as TGS-823, TGS-825, TGS-2611, TGS-816 and TGS-832. Similarly, Table 2 provides us with the best responsive five sensors for onion as TGS-832, TGS-813, TGS-2611, TGS-821 and TGS-826. The two sensors, TGS-832 and TGS-2611, are

found common for both potato and onion. Combining the above findings, the final selection of eight MOS sensors are shown in Table 3.

**Figure 5:** Bar chart showing peak sensor responses for fresh and stale potato.**Figure 6:** Bar chart showing peak sensor responses for fresh and stale onion.**Table 3:** Commodity wise selected list of sensors

Sensor	Commodity
TGS-823	Potato
TGS-825	Potato
TGS-2611	Potato, Onion
TGS-816	Potato
TGS-832	Potato, Onion
TGS-813	Onion
TGS-821	Onion
TGS-826	Onion

**Table 4:** Specifications of the selected sensors

Sensor	VOC Types	Brief Specification
TGS-823	Organic Solvent Vapours	$V_H: 5.0 \pm 0.2V$ $V_C: \text{Max. } 24V$ $R_L: \text{Variable}$ $R_S: 1k\Omega \sim 10k\Omega$
TGS-825	Hydrogen Sulfide	$V_H: 5.0 \pm 0.2V$ $V_C: \text{Max. } 24V$ $R_L: \text{Variable, } 0.45k\Omega \text{ min.}$ $R_S: 3k\Omega \sim 30k\Omega$
TGS-2611	Methane	$V_H: 5.0 \pm 0.2V \text{ AC/DC}$ $V_C: 5.0 \pm 0.2V \text{ DC}$ $R_L: \text{Variable, } 0.45k\Omega \text{ min.}$ $R_S: 0.68 \sim 6.8k\Omega$
TGS-816	Combustible Gases	$V_H: 5.0 \pm 0.2V \text{ AC/DC}$ $V_C: \text{Max. } 24V$ $R_L: \text{Variable}$ $R_S: 5k \sim 15k$
TGS-832	Chlorofluorocarbons (CFC's)	$V_H: 5.0 \pm 0.2V \text{ AC/DC}$ $V_C: \text{Max. } 24V$ $R_L: \text{Variable, } 0.45k\Omega \text{ min.}$ $R_S: 4k\Omega \sim 40k\Omega$
TGS-813	Combustible Gases	$V_H: 5.0 \pm 0.2V \text{ AC/DC}$ $V_C: \text{Max. } 24V$ $R_L: \text{Variable, } 0.45k\Omega \text{ min.}$ $R_S: 5k\Omega \sim 15k\Omega$
TGS-821	Hydrogen Gas	$V_H: 5.0 \pm 0.2V \text{ AC/DC}$ $V_C: \text{Max. } 24V \text{ DC}$ $R_L: \text{Variable, } 0.45k\Omega \text{ min.}$ $R_S: 1k\Omega \sim 10k\Omega$
TGS-826	Ammonia	$V_H: 5.0 \pm 0.2V \text{ AC/DC}$ $V_C: \text{Max. } 24V \text{ DC}$ $R_L: \text{Variable}$ $R_S: 20 \sim 100k\Omega$

where,

$V_H$ : Heater voltage       $V_C$ : Circuit voltage  
 $R_L$ : Load resistance       $R_S$ : Sensor resistance

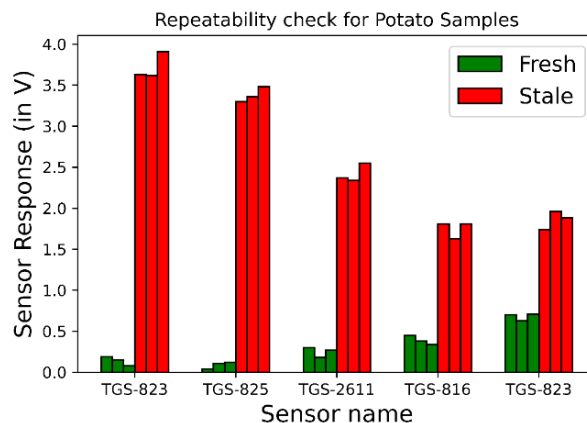
The e-POT sensor array contains the eight sensors as depicted in Table 3, and all these sensor values are considered during the analysis of the health condition of both the cases of potato and onion. Table 4 summarizes the brief specifications of the selected eight sensors.

In order to check the performance of the selected sensors in differentiating fresh and rotten potatoes and onions, a measurement system analysis (MSA) is carried out to check the repeatability of the sensors. We made three measurements for each of the samples and a histogram of the sensor responses are shown in Figure 7 and Figure 8 for potato and onion respectively. Both the plots show that the sensor responses are repetitive with standard deviations for all the sensors are in the order of 0.1 or less.

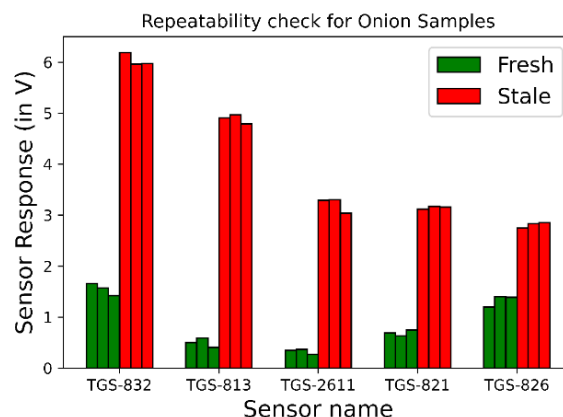
### FABRICATION OF E-NOSE FOR THE APPLICATION

Machine olfaction or e-nose schemes are to some extent similar to the human olfactory system. We need a Sampler or an Odour Handling and Delivery Unit to capture the volatile odour molecules and pass them to an array of sensors; individual sensors in the array work similar to the human odour receptors in sensing the odour volatiles. The signal conditioning and data pre-

processing module reduce the dimension of the dataset for analysis similar to secondary neurons or glomerulus in the human case. Finally, soft computing or pattern recognition engine mimics the role of the human brain, i.e., to perceive the pattern of the odorants.



**Figure 7.** Histogram to show repeatability of the selected sensors in detecting fresh and stale potato

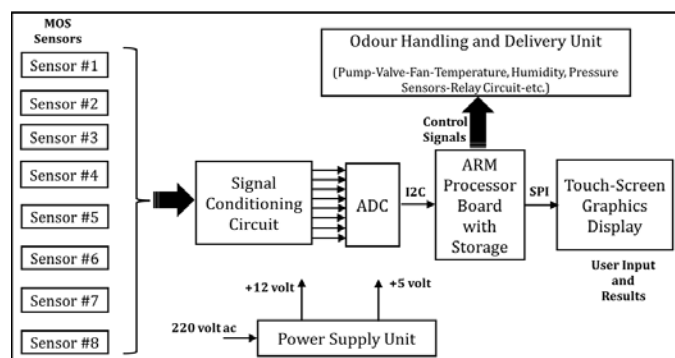


**Figure 8.** Histogram to show repeatability of the selected sensors in detecting fresh and stale onion

The majority of the commercially available electronic noses require manual intervention to place the sample into the sample chamber, and the operation is mainly carried out in batch mode. However, this application of checking the health of stored vegetables demands online monitoring without any sort of human involvement. This drives us to design and develop an e-Nose specific to this application. The circuitry and software program of the developed machine olfaction device, named e-POT, is described in this section. Eight metal oxide semiconductor sensors (MOS), namely, TGS-816, TGS-2611, TGS-821, TGS-825, TGS-813, TGS-826, TGS-823 and TGS-832, are utilized to build a sensor array. MOS sensors are chosen because of their performance, commercial availability and long-term stability. When MOS sensors are exposed to VOCs, the resistances of the sensors change depending upon the amount of VOCs, and these changes in resistance need to be captured as sensor responses. By making a simple resistive divider circuit, this resistance change

is captured in terms of change in voltage. The next stage is the signal conditioning stage, built on industry-standard LMC6001 Instrumentation Amplifiers for amplification, attenuation and/or buffering of sensor signals. LMC6001 is an electrometer amplifier with an input current as low as 25 fA and is ideally suited for high impedance sensors. The other advantage of this OPAMP is that it can be operated from a single supply, thus making the Power Supply requirement more straightforward. This high-end amplifier is used here to make the system more generic to cater diverse range of sensors. It also has a higher signal-to-noise rejection ratio. For filtering of the sensor signal, a simple RC low pass filter is used. Attenuation of signals to make them compatible with the microcontroller I/O pins is done through a resistive divider followed by an active buffer stage. Analog-to-Digital Conversion (ADC) is achieved by using external ADC, ADS1115. It is a low power 16-bit delta-sigma ADC and connected to the processor through an I2C interface. An input multiplexer along with sample-and-hold circuits selects the four analogue channels sequentially. Two such ADCs are added to the same I2C line to increase the number of analogue channels to eight. Individual ADCs are selected through the address lines.

A 32-bit ARM processor-based board is used as the heart and brain of the device. The sensor signals are captured through the I2C interface and are processed and stored on this board. The software program is written in Java and C on the Linux operating platform. A 7-inch touch screen display device is interfaced with the board as User Interface. Captured sensor data is stored date-wise in a low-footprint open-source database named Derby. Other components used in the device are micropumps, valves, pressure sensors, temperature and humidity sensors, and fans to construct the device's odour handling and delivery component. The processor input-output lines employing relay circuits are controlled through these devices. A power adapter with 12-volt and 5-volt outputs supplies power to the device. Figure 9 portrays the block diagram of the circuit.

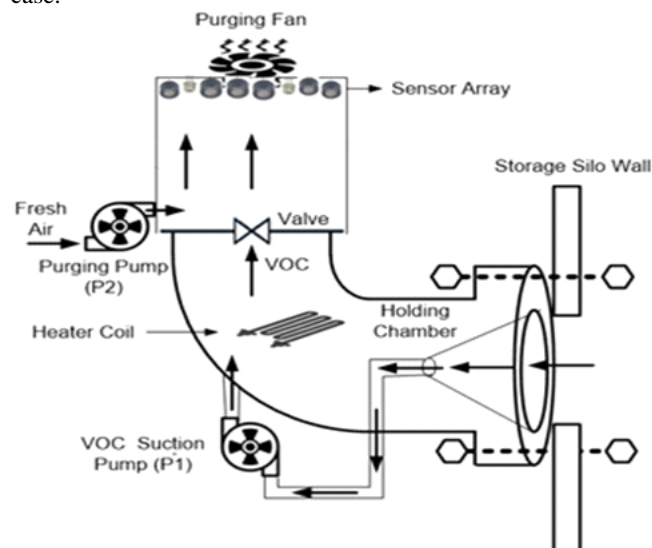


**Figure 9.** Block Diagram of the developed Machine Olfaction Device, e-POT.

The odour delivery requirement and hence the mechanism is unique in this application. In most e-Nose applications, there is no requirement for continuous operation. During testing of a sample, it is generally placed in a sample chamber close to the

sensor array so that the odour volatiles can easily be sniffed and exposed to the sensors. But the requirement here is continuous  $24 \times 7$  operations and to sniff odour volatiles from the cold storage silo for analysis at certain time intervals.

The working principle of the MOS sensor is stated as follows. During measurement, the non-polar volatile molecules are adsorbed at the surface of the semiconductor, where they are oxidized or reduced with oxygen, causing a modification of the resistance or conductivity of the device. This occurs only at a high temperature ( $300 - 450 \text{ }^\circ\text{C}$ ) and is regarded as the working temperature of MOS sensors.<sup>30</sup> This is the reason for employing an internal heater element inside the MOS sensor. The sniffed and captured odour molecules from the cold storage chambers are cold. If delivered directly to the sensors, the sensors would give erratic responses as these cold molecules reduce the temperature of the sensor surface, thereby changing the characteristics of the resistance values. To neutralize this effect, it is required to bring back the captured odour VOCs close to  $30 - 40 \text{ }^\circ\text{C}$  temperature. Since the VOCs are heated up to ambient temperature, the characteristics of the VOCs are expected not to dissociate in this case.

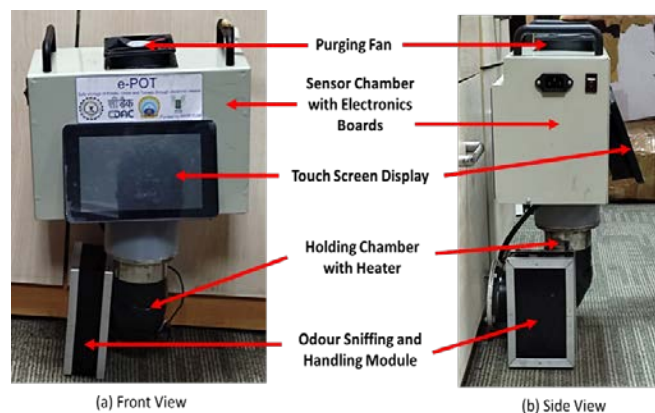


**Figure 10.** Schematic Diagram of the Odour Handling and Delivery Unit of e-POT device.

A specialized arrangement is made to meet all of these requirements and the general conditions of e-nose sampling. The L-shaped cylindrical chamber, termed as holding chamber, is the VOCs pathway between the storage silo and the sensor chamber. The volume of this chamber is 250 cc. The holding chamber is mounted between the silo wall and sensor chamber. The VOCs are sniffed through a 1-inch small hole made at the wall of the silo. A micro suction pump (P1) is used to sniff VOCs from the silo through a funnel and place VOCs inside the holding chamber until the pressure inside the chamber reaches 500 mm of Hg. The building of pressure is monitored using a pressure sensor.

The holding chamber is heated to  $30 - 40 \text{ }^\circ\text{C}$  for 2 minutes to raise the temperature of the collected VOCs. When the VOCs are exposed to the sensors by opening a valve, the processor hardware-software captures and stores sensor data. After that, the

sensors are purged so that they can go back to their base values. The micro-pump (P2) and the purging fan are utilized for this purpose. The pump sucks fresh air from the ambient environment, puts it on the sensor heads, and the fan takes the air out of the sensor chamber, thereby cleaning the sensor heads. This entire cycle repeats at an interval of 30 minutes or as configured by the user. A schematic diagram of this odour handling and delivery unit is shown in Figure 10. The photograph of the developed e-POT device is shown in Figure 11.



**Figure 11.** Photograph of the developed e-POT device.

### EXPERIMENTAL SET-UP AND SAMPLE COLLECTION

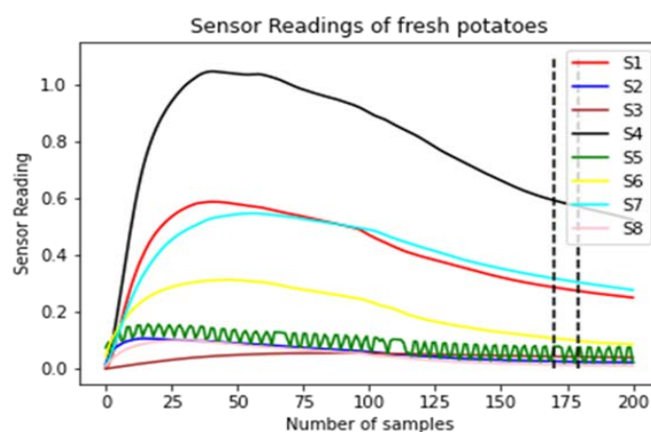
A cold storage unit of approximately 19000-litre capacity and with temperature and humidity control facilities has been set up at CIAE, Bhopal, for this study. Additionally, a 500-litre storage chamber is utilized at C-DAC, Kolkata, for the study. Arrangements are made in both units to fit the e-POT device for the health study of stored potatoes and onions. Experiments had been conducted at both of these facilities.

During the study, sample collection is done by fitting the e-POT suction port to the VOC sampling port of the cold chamber simply through a nut and bolt arrangement. Using the touch screen of e-POT, the device is configured for the type of the stored commodity by navigating a user-friendly GUI, and the device is asked to 'run'. The e-POT device then starts capturing VOC samples with database storing and analysis of eight sensor data at an interval of every 30 mins. This sampling interval can be adjusted depending upon the commodity type and use case through the initial e-POT configuration. The operations inside e-POT for each of these sampling are done in four steps (i) sniffing of VOCs from the chamber for 60 sec until the pressure inside the holding chamber reaches 500 mg of Hg, (ii) heating the trapped VOCs for 120 sec, (iii) exposing the VOCs to sensor array and capturing sensor data for 20 sec (200 samples per sensor at a sampling rate of 100 ms) and finally (iv) purging of the sensors for 120 sec so that they go back to their base values. The total time taken by e-POT from the start of sniffing to sensor purging in every cycle is 320 sec in total. e-POT then remains idle for 30 min, and this process is repeated. The eight sensors selected and fabricated in this potato and onion health study are depicted in Table 5.

**Table 5:** Sensors used in e-POT for potato and onion health study.

Sensor Number	S1	S2	S3	S4	S5	S6	S7	S8
Sensor Name	TGS 816	TGS 2611	TGS 821	TGS 825	TGS 813	TGS 826	TGS 823	TGS 832

The sensor readings of stored potato samples in a single sampling cycle are illustrated in Figure 12. The plots of all other samples and commodities are similar to that of Figure 12 but with different slopes and different saturation points based on health status and commodity types. Out of the eight sensors of e-POT, the records of six sensors are taken for analysis discarding sensor numbers S3 and S5, as, during experimentation, the sensitivity of S3 is found to be very low and S5 giving a jittery response.



**Figure 12.** Sensor Readings of stored potato samples in one cycle.

### METHODS UNDERTAKEN IN THE STUDY

As stated in the "Introduction Section", this study is conducted in two phases, in a 500-litre storage container at C-DAC, Kolkata, in the first phase and in a 19000-litre experimental cold storage chamber at CIAE, Bhopal, in the second phase. The details of the experiment and data analysis methodologies are described in this section.

### Study to check the efficacy of the e-POT device in differentiating 'fresh' and 'stale' commodities from VOC signatures:

The aim of this study is to find out the effectiveness of the developed e-POT system in differentiating VOCs effused from fresh and stale commodities and to find out commodity wise distinct threshold level, termed as "decay point" indicating the start of spoilage or presence of small quantities of spoiled vegetables along with fresh ones. This study establishes not only the efficacy of the e-Nose but also the effectiveness of selected sensors and the specially designed odour capturing, handling and delivery unit for stored vegetable health determination applications. Two such experiments are carried out, one with potato samples for about four and half days and another one with onion samples for over seven days. In both cases, the e-POT is made to run continuously in 24x7 mode, and sensor data are



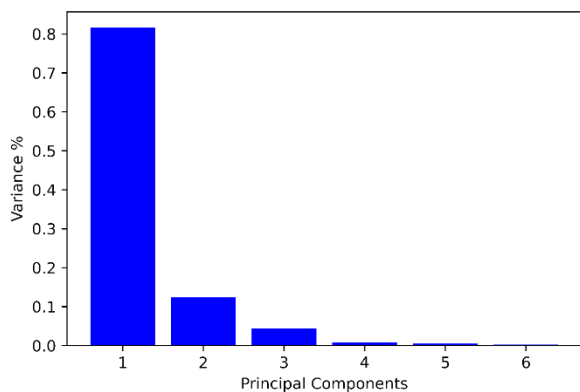
captured at an interval of 60 minutes for analysis. As stated earlier, two sensors, S3 and S5, are discarded from analysis for obvious reasons (as stated earlier) so that we have 6-dimensional data obtained from 6 sensors for analysis.

First, the result of analysis for our experiment with potatoes is described. For “decay point” determination, we need to reduce this 6-dimensional dataset to a single dimension and coin this uni-dimensional data as “odour index” for potato. Finally, the “odour index” is plotted in a graph with respect to time. In order to reduce the dimensionality of the dataset, the correlations among the different sensors are calculated, as shown in Figure 13. It is observed that the different sensor readings are highly correlated, hence reduction of dimension to one would be able to retain a major portion of information.

	S1	S2	S4	S6	S7	S8
S1	1.000000	0.450012	0.948861	0.777434	0.947517	0.928666
S2	0.450012	1.000000	0.414203	0.633341	0.503015	0.648807
S4	0.948861	0.414203	1.000000	0.697420	0.942604	0.877734
S6	0.777434	0.633341	0.697420	1.000000	0.810489	0.908049
S7	0.947517	0.503015	0.942604	0.810489	1.000000	0.937427
S8	0.928666	0.648807	0.877734	0.908049	0.937427	1.000000

**Figure 13.** Correlation among the sensor data.

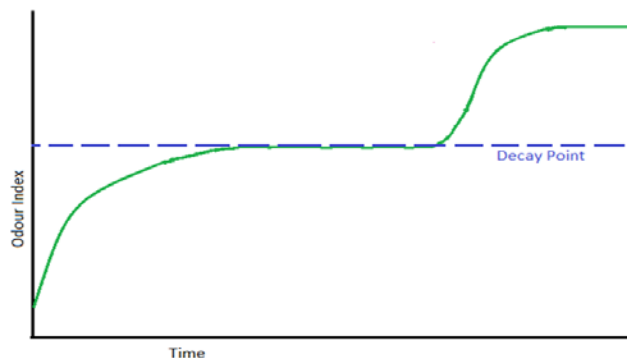
The data is then normalized and Principal Component Analysis (PCA) is conducted. Figure 14 depicts that more than 85% of information is explained by Principal Component 1. Hence, Principal Component 1 is termed as “odour index” and is considered for plotting and analysis.



**Figure 14.** Ratio of Variance explained by Principal Components of Sensor data.

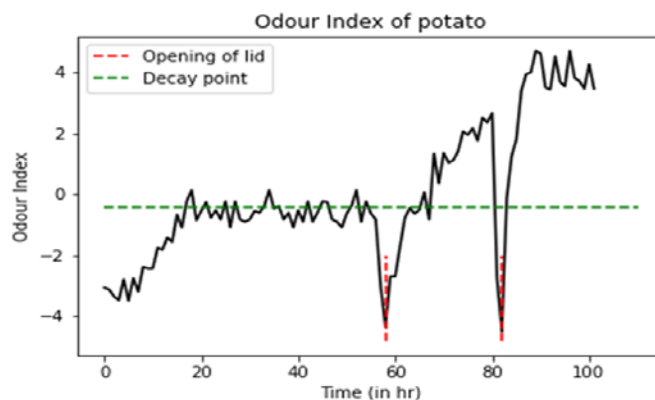
Ideally, once the storage chamber is filled with fresh potato samples, the sensor readings should start to increase until it gets saturated to a stable value, which may be marked as “threshold level”. If a small portion of the potato starts to rot or a small quantity of stale potato is added to the chamber, the sensor values should shoot up this threshold level as is found from GC-MS analysis in which we found that VOC concentration becomes very high in spoilt and infected potatoes compared to fresh ones. The point at which the odour index starts increasing above the

“threshold”, can be marked as the “decay point” and the storage supervisor may be alarmed. Figure 15 shows the expected ideal plot of odour index with respect to time if the storage unit is left undisturbed.



**Figure 15.** Expected ideal plot of odour index with respect to time.

This study started with 5 kg of fresh potato in the 500-litre cold storage chamber, and observation is made for about two and half days to notice that VOC signals really settle to the saturation level. Once this saturation is observed, 200 g of stale potato is added into the storage chamber. After waiting for a day, 200 g of stale potato is added again to observe the results. When the computed odour index is plotted against time, the graph as shown in Figure 16 is obtained. The plot shows saturation of odour index, i.e., the odour index reaching to threshold level well within 24 hours. When the first-time stale potato is added, an increase of odour index value well above this threshold level is observed and then attains to another new saturation value within 24 hours. On addition of stale potato the second time, the odour index surpasses the second saturation level and attains a new saturation level. This plot clearly corroborates with the increase of VOC concentration as the quantity of spoilt sample or level of spoilage increases. The sudden dips in the plot are due to the opening of lids during the addition of stale samples into the chamber. As the lid of the 500-litre storage is at the top side, the opening of the lid causes the majority of the generated VOCs to escape out, thereby reducing the concentration of VOC inside the chamber. The first saturation level can be marked as the ‘decay point’ for potatoes,



**Figure 16.** Odour Index plot of potato for approximately 100 hours.

and a few other discrete levels may be identified to predict the degree of spoilage and/or quantity of stale potatoes inside the storage chamber.

The experiment with onion is done just in the reverse way, i.e., the experiment is started with 5 kg of fresh samples added with 200 g of stale onions. After approximately five and half days, when the VOC values of this mix saturate to a stable value, the stale onions are removed, keeping only fresh ones inside the chamber. The objective is to check whether the VOC level comes down to some lower level as is expected as per GC-MS detection of VOC levels. The 200×6 dataset at each instance of time is reduced to a single value by determining the dominant or largest Eigenvalue of the matrix using the Vector Iteration method. This value is named as “Normalized Odour Index”. The normalized odour index is plotted with respect to time as shown in Figure 17. The plot clearly shows the return of the sensor values to a somewhat lower level and saturates to the level of ‘decay point’ of onion. Again, the abnormal dip in the plot is due to the opening of the topside lid during the removal of stale onions and the escape of VOCs.

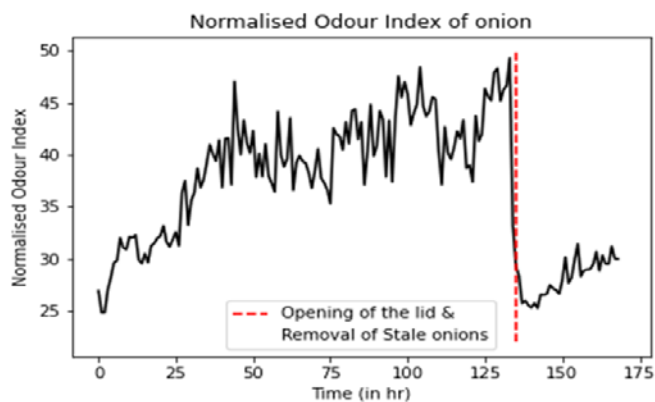


Figure 17. Normalized Odour Index plot of onions for 7 days.

### Study towards ‘Classification’ and ‘Prediction’

The second phase of the study is conducted with e-POT fitted to the 19000-litre cold storage chamber at CIAE, Bhopal, on potato and onion samples. The first aim of this study is to identify the presence of traces of spoil or infected vegetables in the chamber employing different classification algorithms, and to find out the best-suited algorithm for this use case. Another object of this study is to map the sensor data with the VOC concentration of potato and onion samples infected by certain microorganisms as obtained from GC-MS analysis and to predict the level of staleness of the stored commodity. In both of these studies, 90 datasets (VOC values) of potato samples and 270 datasets of onion samples are recorded. From each of these datasets, the average of nine consecutive rows (170th to 179th row) of each dataset, where the sensor readings are stable, are taken into account for analysis.

#### Classification Study

Classification models refer to algorithms used for categorizing unknown samples into different groups based on the training of a

labelled dataset. We have trained the device using Probabilistic Neural Network (PNN) and Partial Least Square (PLS) classification algorithms with the sensor data of e-POT to categorize potato and onion samples. The models are tested in 10 cross-fold validation.

#### (a) Probabilistic Neural Network (PNN) Classification

Probabilistic Neural Network (PNN) classifier<sup>31,32</sup> uses kernel discriminant analysis in which the operations are organized into a multi-layered feedforward network with four different layers. It guarantees to converge to an optimal classifier when the dataset is considerably large and is insensitive to outliers. The algorithm for PNN classifier is given in Figure 18.

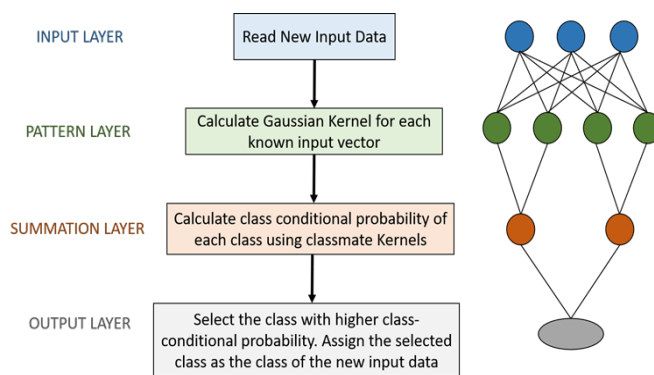


Figure 18. Algorithm of PNN Classifier.

#### (b) Partial Least Square (PLS) Classification

Partial Least Square (PLS)<sup>33</sup> is an optimal regression algorithm based on covariance. We have applied the thresholding technique on the predicted output of PLS regression to obtain binary classification<sup>34</sup> of unknown samples into “fresh” and “stale” classes. PLS applies dimension reduction of the samples (similar to PCA) before applying a linear regression algorithm on the transformed data. In an initial study, it was observed that the dataset contains a significant percentage of outliers, and hence, PLS is chosen for classification. Figure 19 depicts the algorithm for classification using PLS.

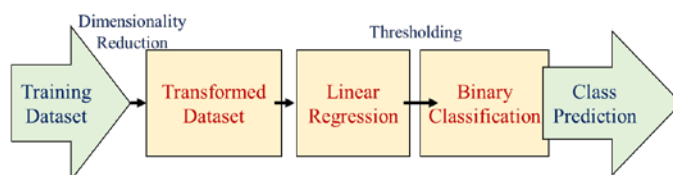


Figure 19. Algorithm for PLS Classifier.

#### Prediction Study

The GC-MS results for the calculation of the concentration of major VOCs in the fresh and infected commodities are given in Table 6 and Table 7.

Regression model is applied to establish a relationship between the independent variables, i.e., the sensor values and the dependent variables, i.e., the measure of VOCs emitted by the

**Table 6:** Major VOCs of potato inoculated with *Erwinia carotovora*.

Name of VOCs	Concentration in fresh potatoes (ppm)	Concentration in infected potatoes (ppm)
Hexanoic acid, butyl ester	6500	20320
1-Butanol	1600	37800

**Table 7:** Major VOCs of onion inoculated with *Erwinia carotovora*.

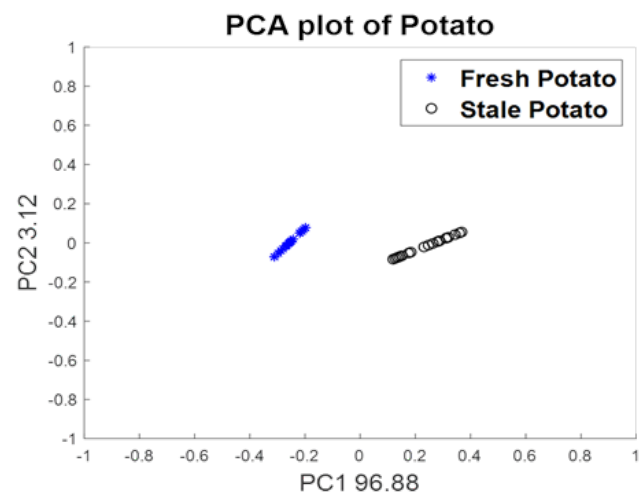
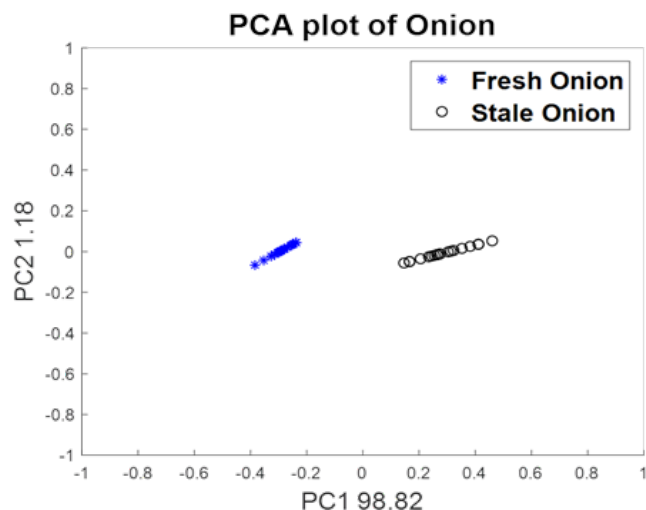
Name of VOCs	Concentration in fresh onions (ppm)	Concentration in infected onions (ppm)
3-Bromo Furan	300	2300
Ethyne, fluoro-	0	63500

vegetables when fresh and inoculated by the microorganism *Erwinia carotovora* of the training dataset. For ease of computation, the relationship between the independent variables and the target(s) is assumed to be linear. An approximate prediction of the concentration of VOCs of unknown samples are done, and based on these predictions, the degree of spoilage of the commodities are estimated. However, the precision of this model cannot be evaluated due to the unavailability of GC-MS results for each intermediate stage of infection and spoilage, but it can accurately categorize the test samples into “fully spoilt”, “partially spoilt” and “fresh” categories.

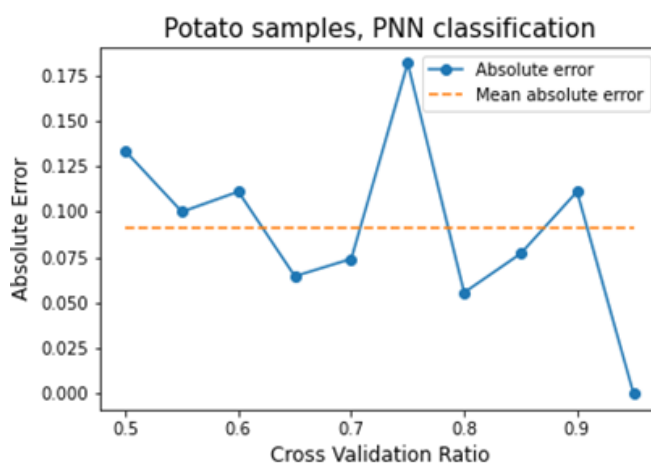
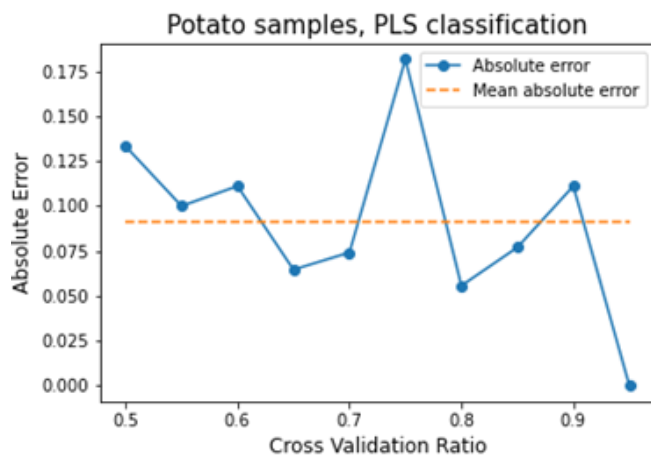
## RESULTS AND ANALYSIS

### Result of “Clustering”

Figure 20 and Figure 21 show the PCA plots of fresh and state potatoes and fresh and stale onions, respectively. The plots clearly establish very good clustering abilities of the sensors in the array.

**Figure 20.** PCA plot of fresh and stale potato samples.**Figure 21.** PCA plot of fresh and stale onion samples.

### Result of “Classification Study”

**Figure 22.** Error Analysis of PNN classifier for potato samples.**Figure 23.** Error Analysis of PLS classifier for potato samples.

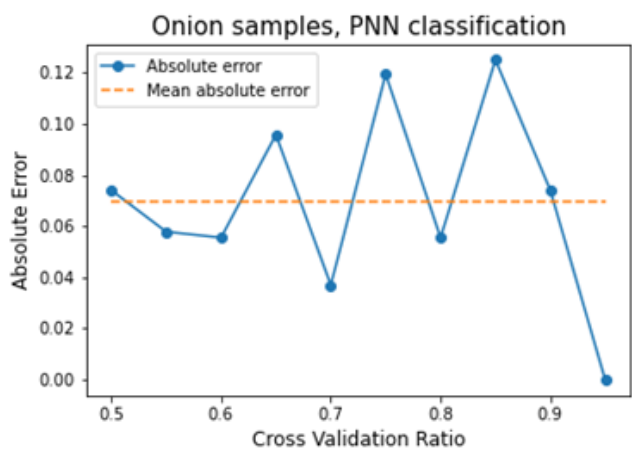


Figure 24. Error Analysis of PNN classifier for onion samples.

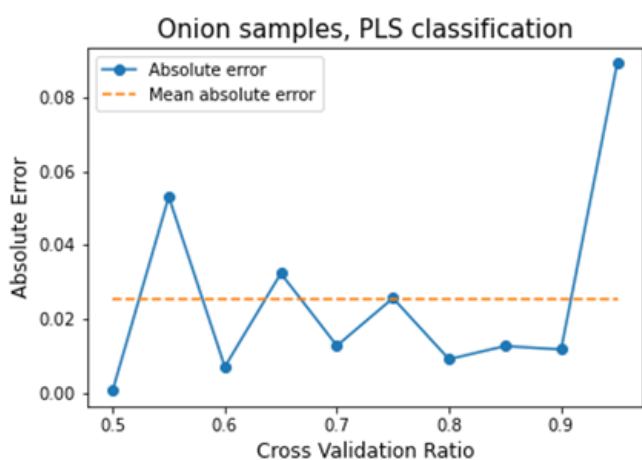


Figure 25. Error Analysis of PLS classifier for onion samples.

Figure 22 and Figure 23 show the absolute error of classification of potato as “fresh” and “stale” by executing PNN and PLS classifiers, respectively, over various cross-validation ratios, i.e., the ratio of the number of training samples to that of test samples. Figure 24 and Figure 25 represent the same for onion samples.

The comparison for results of binary classification of fresh and stale vegetables are shown in Table 8. This is clear that the PLS classifier is more accurate as compared to the PNN algorithm for our use case.

Table 8: Accuracy of Classification models.

Classification Algorithm	Vegetable	Accuracy (%)
Probabilistic Neural Network (PNN)	Potato	90.92
	Onion	93.06
Partial Least Square (PLS)	Potato	99.45
	Onion	97.46

## Result of “Prediction Study”

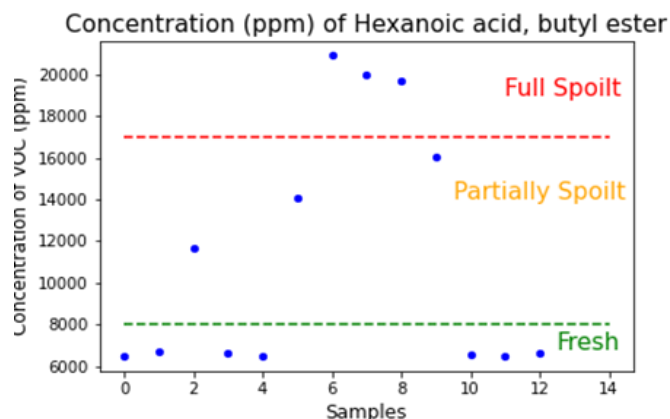


Figure 26. Predicted Concentration of Hexanoic acid, butyl ester in potato samples inoculated with *Erwinia carotovora* and three discrete spoilage levels.

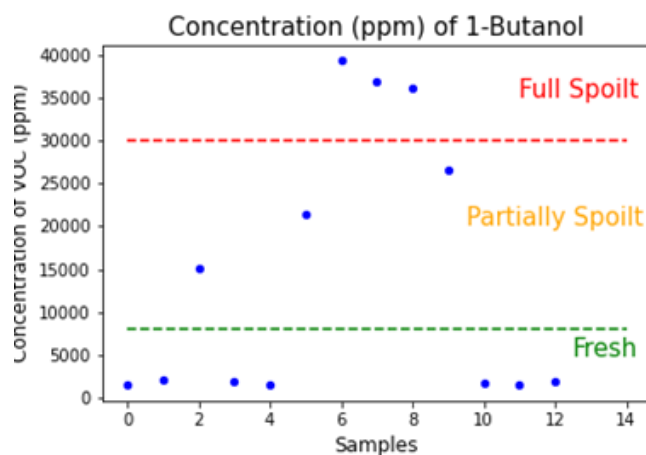


Figure 27. Predicted Concentration of 1-Butanol in potato samples inoculated with *Erwinia carotovora* and three discrete spoilage levels.

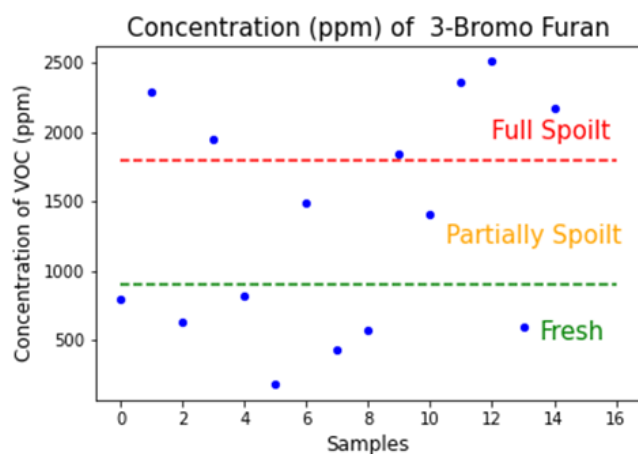
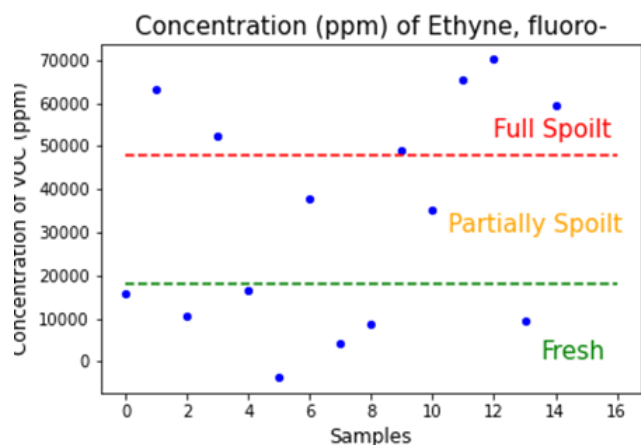


Figure 28. Predicted Concentration of 3-Bromo Furan in onion samples inoculated with *Erwinia carotovora* and three discrete spoilage levels.



**Figure 29.** Predicted Concentration of Ethyne, fluoro- in onion samples inoculated with *Erwinia carotovora* and three discrete spoilage levels.

Figure 26 and Figure 27 show the predicted concentrations of major VOCs emitted by potato samples when inoculated with *Erwinia carotovora* at different stages of infection. Figure 28 and Figure 29 show the same for onion samples. The model is validated with known samples and can accurately predict the degree of infection. However, the precision in concentration of VOCs predicted cannot be measured due to the lack of GC-MS results for each intermediate stage of infection.

## CONCLUSION

The present work on continuous, online and in-situ freshness detection of stored vegetables through VOC sensing employing electronic nose is the first of its kind in India and proves to have huge potential. The performance of the developed e-POT device is found to be very stable and repetitive and has applicability in other continuous VOC monitoring applications. The study shows that after storage, fresh potato VOC starts to increase and reaches a saturation value. When the VOC value shoots up and crosses this saturation level by some noticeable margin, it indicates the presence of spoilage traces inside the storage chamber. Study with onion shows that if we can remove the stale commodities from the storage chamber, the VOC level, otherwise at a higher level, comes down again to the saturation level indicating the presence of only fresh onions inside the chamber.

The classification accuracy obtained for fresh and stale samples are quite high, 99.45% and 97.46% for potato and onion, respectively. Our analysis predicts the concentration of certain chemicals and thereby spoilage stages (three discrete stages in this study) from VOC sensor data. The correctness of chemical concentration prediction cannot be validated as simultaneous GC-MS of headspace data cannot be carried out for all intermediate stages. However, the prediction of three discrete states of spoilage for both potato and onion are accurate.

As a future scope, this work may be extended to other fruits and vegetables to announce alarms at the start of decay so that timely corrective actions can be taken. Correlation of spoilage percentage or degree of staleness with GC-MS determined VOC

levels at different stages is another scope of future study. The addition of temperature and RH sensors in e-POT may help monitor these two very important parameters inside the chamber that would be helpful in taking corrective measures. As spin-off technology, this work can be customized and extended for household and hotel/restaurant refrigeration applications to monitor the health of stored food and raw food materials.

## ACKNOWLEDGMENTS

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## CONFLICT OF INTEREST

Authors declared no conflict of interest.

## REFERENCES AND NOTES

- MoA&FW. Contribution of Agriculture Sector towards GDP. **2021**. <https://pib.gov.in/PressReleaseDetail.aspx?PRID=1767038>.
- MOSPI. Ministry of Statistics and Programme Implementation. **2021**. <https://statisticstimes.com/economy/country/india-gdp-sectorwise.php>.
- A. Desai. Case study on potential for scaling up: "Waste to wealth by incubating mini cold storage technology ventures" in India. *World Bank*. **2011**, 29, 2013.
- A.A. Kader. In *V International Postharvest Symposium 682* 2004, p 2169-76.
- V. Paul, R. Ezekiel, R. Pandey. Cold storage in India: present scenario and future directions. *Process Food Ind.* **2016**, 19, 25-28.
- S. Tiwari, A. Kate, D. Mohapatra, M.K. Tripathi, H. Ray, A. Akuli, A. Ghosh, B. Modhera. Volatile organic compounds (VOCs): Biomarkers for quality management of horticultural commodities during storage through e-sensing. *Trends Food Sci. Technol.* **2020**, 106, 417-33.
- H.J. McDermott. Air monitoring for toxic exposures, John Wiley & Sons, **2004**.
- G. Monitors. Model IR400: Infrared point detector for combustible gas detection. **2011**. <https://www.automation.com/en-us/products/product17/general-monitors-announces-ir400-combustible-gas-d>.
- M.-S. Instruments. RAE Systems. **2011**. <https://www.midstateinstruments.com/rae-systems-toxirae-pro-le/>.
- H.-J. Hübschmann. Handbook of GC-MS: fundamentals and applications, John Wiley & Sons, **2015**.
- J. de Gouw, C. Warneke, T. Karl, G. Eerdeken, C. van der Veen, R. Fall. Sensitivity and specificity of atmospheric trace gas detection by proton-transfer-reaction mass spectrometry. *Int. J. Mass Spectrom.* **2003**, 223, 365-82.
- J.R. Gosz, D.I. Moore, C.N. Dahm, S. Hofstadler. Field testing long-path Fourier transform infrared (FTIR) spectroscopy for measurements of atmospheric gas concentrations. *Remote Sens. Environ.* **1990**, 32, 103-10.
- D. Karakaya, O. Ulucan, M. Turkan. Electronic nose and its applications: a survey. *Int. J. Autom. Comput.* **2020**, 17, 179-209.
- A. Das, T.K. Ghosh, A. Ghosh, H. Ray. In *2012 Sixth International Conference on Sensing Technology (ICST)* 2012, p 577-82.
- A. Ghosh, H. Ray, T.K. Ghosh, A. Das, N. Bhattacharyya. Generic Handheld E-Nose Platform for Quality Assessment of Agricultural Produces and Biomedical Applications. *Chem. Eng. Trans.* **2014**, 40, 259-64.
- S. Romani, C. Cevoli, A. Fabbri, L. Alessandrini, M. Dalla Rosa. Evaluation of coffee roasting degree by using electronic nose and artificial neural network for off-line quality control. *J. Food Sci.* **2012**, 77, C960-C65.

17. R.S. Lima, G.C. Danielski, A.C.S. Pires. Mastitis detection and prediction of milk composition using gas sensor and electrical conductivity. *Food Bioproc. Tech.* **2018**, 11, 551-60.
18. J.S. Vestergaard, M. Martens, P. Turkki. Application of an electronic nose system for prediction of sensory quality changes of a meat product (pizza topping) during storage. *LWT.* **2007**, 40, 1095-101.
19. P.-F. Qi, Q.-H. Meng, M. Zeng In *2017 ISOCS/IEEE International Symposium on Olfaction and Electronic Nose (ISOEN)*; IEEE: 2017, p 1-3.
20. T. Majchrzak, W. Wojnowski, T. Dymerski, J. Gębicki, J. Namieśnik. Electronic noses in classification and quality control of edible oils: A review. *Food chem.* **2018**, 246, 192-201.
21. Y. Yin, Y. Hao, Y. Bai, H. Yu. A Gaussian-based kernel Fisher discriminant analysis for electronic nose data and applications in spirit and vinegar classification. *J. Food Meas. Charact.* **2017**, 11, 24-32.
22. J. Tan, W.L. Kerr. Determining degree of roasting in cocoa beans by artificial neural network (ANN)-based electronic nose system and gas chromatography/mass spectrometry (GC/MS). *J. Sci. Food Agric.* **2018**, 98, 3851-59.
23. H. Ray, N. Bhattacharyya, A. Ghosh, B. Tudu, R. Bandyopadhyay, A. Ghosh, S.P. Biswas, S. Majumdar. Fragrance profiling of Jasminum sambac Ait. flowers using electronic nose. *IEEE Sens. J.* **2016**, 17, 160-68.
24. S. Dragonieri, R. Schot, B.J. Mertens, S. Le Cessie, S.A. Gauw, A. Spanevello, O. Resta, N.P. Willardet. al. An electronic nose in the discrimination of patients with asthma and controls. *J. Allergy Clin. Immunol.* **2007**, 120, 856-62.
25. B.S. Chhikara, R. Kumar, Poonam, P. Bazard, R.S. Varma. Viral infection mitigations using advanced nanomaterials and tools: lessons from SARS-CoV-2 for future prospective interventions. *J. Mater. Nanosci.* **2021**, 8 (2), 64-82.
26. D.-M. Wong, C.-Y. Fang, L.-Y. Chen, C.-I. Chiu, T.-I. Chou, C.-C. Wu, S.-W. Chiu, K.-T. Tang In *2018 IEEE International Conference on Applied System Invention (ICASI)*; IEEE: 2018, p 1119-20.
27. R. Fend, A.H. Kolk, C. Bessant, P. Buijtels, P.R. Klatser, A.C. Woodman. Prospects for clinical application of electronic-nose technology to early detection of Mycobacterium tuberculosis in culture and sputum. *J. Clin. Microbiol.* **2006**, 44, 2039-45.
28. C.M. Robroeks, J.J. van Berkel, J.W. Dallinga, Q. Jöbsis, L.J. Zimmermann, H.J. Hendriks, M.F. Wouters, C.P. van der Grintenet. al. Metabolomics of volatile organic compounds in cystic fibrosis patients and controls. *Pediatr. Res.* **2010**, 68, 75-80.
29. T. Straume, D. J Loftus, J. Li, M. A Coleman, C. E Davis, K. A McMonigal, M. Piccini, A. K Singh. Biomarker-detection technologies for comprehensive medical diagnosis during deep-space missions. *Recent Patents on Space Technology.* **2013**, 3, 13-23.
30. C. Wang, L. Yin, L. Zhang, D. Xiang, R. Gao. Metal oxide gas sensors: sensitivity and influencing factors. *Sensors.* **2010**, 10, 2088-106.
31. I.M. El Emary, S. Ramakrishnan. On the application of various probabilistic neural networks in solving different pattern classification problems. *World Appl. Sci. J.* **2008**, 4, 772-80.
32. K. Bhosle, B. Ahirwadkar. Deep learning Convolutional Neural Network (CNN) for Cotton, Mulberry and Sugarcane Classification using Hyperspectral Remote Sensing Data. *J. Integr. Sci. Technol.* **2021**, 9 (2), 70-74.
33. M. Larbi, R. Trincherro, F.G. Canavero, P. Besnier, M. Swaminathan In *2020 IEEE 24th Workshop on Signal and Power Integrity (SPI)*; IEEE: 2020, p 1-4.
34. M. Stocchero, M. De Nardi, B. Scarpa. PLS for classification. *Chemometr. Intell. Lab. Syst.* **2021**, 216, 104374.