Makarichian *et al.*
Food Production, Processing and Nutrition (2024) 6:52
https://doi.org/10.1186/s43014-024-00235-7

Food Production, Processing and Nutrition

RESEARCH

Use of E-Nose in inspecting the effect of processing type on the aroma of garlic (*Allium Sativum L.*): a critical hint in the quality assessment

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Abstract

Controlling the quality and health of foodstuffs is of great importance. The quality of foods like garlic is strongly influenced by the conditions of processing. Fungal infection is one of the most common hazards of garlic productivity that can affect its processing as well. This research aimed to use the E-Nose to investigate the aroma of garlic as a quality control factor influenced by different treatments such as type of processing, type of fungal infection, and time elapsed since the date of inoculation. The data was investigated and categorized through different methods such as principal component analysis (PCA), linear discriminant analysis (LDA), Support vector machine (SVM), and backpropagation neural network (BPNN). The Index of deterioration toughness increased during the monitoring period. In the analysis of the data related to the unprocessed whole (UW), dried slices (DS), garlic powder (PO), and garlic tablet (TA), the PCA included 55%, 75%, 47%, and 53% of the data, respectively. The LDA was able to classify the aroma of UW, DS, PO, and TA samples based on the TFI treatment with an accuracy of 90%, 93.33%, 88.89%, and 60%, respectively. Also, the BPNN classified the aromas of UW, DS, PO, and TA samples based on the TEI treatment with an accuracy of 90%, 95.6%, 72.2%, and 82.2%, respectively. The results revealed that the aroma alteration can be used as a comprehensive factor in the quality control of processed products. As well, the type of processing had significant effects on the severity of decay caused by fungal infection.

Keywords E-Nose, Fung, Garlic, Processing, Quality

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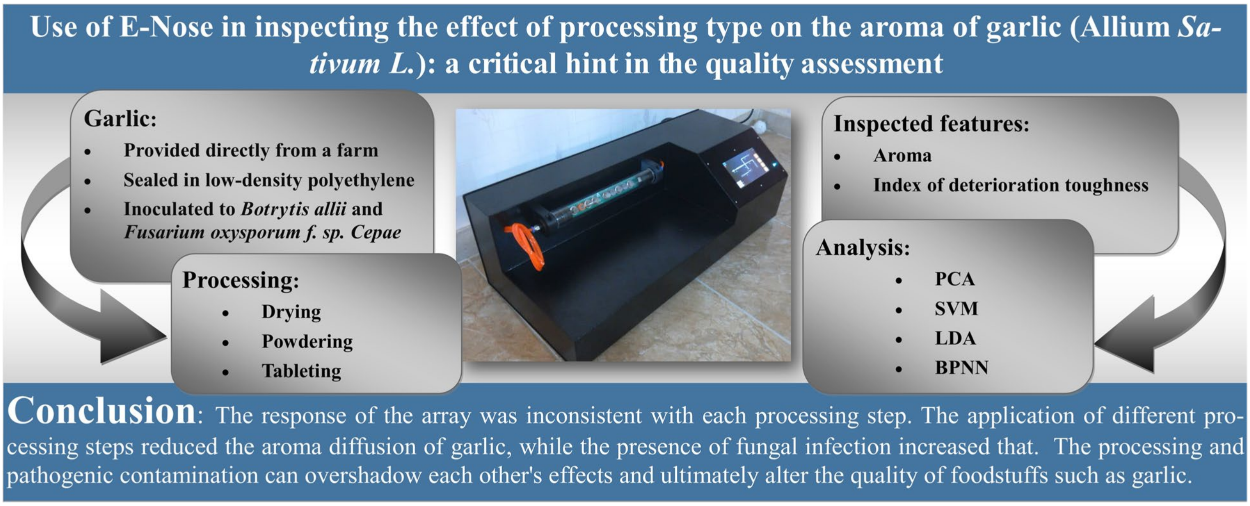
Graphical Abstract



Background

Quality has a key role in the markets of foodstuffs and guarantees consumer acceptability. The concept of quality posturizes itself as parameters like physical and functional attributes, chemical structure, organoleptic characteristics, nutritional importance, the existence of contaminants, and also consumer approval. The quality of food is the main basis of its safety which has excessive disturbance especially when it comes to social wellness (Zhang et al. 2020). Nowadays, new foodstuffs develop and present to the market which are processed with resulted quality variations (Mihafu et al. 2020). Besides, consumers are dramatically aware of the presence of potential hazards in their foods and claim a stable supply of high-quality foodstuffs. The employment of quality assessment is crucial to the standardization of all steps along the food supply chain and to guarantee that raw materials and finished products are processed according to the necessary criteria (Janaki alias Priya and Chathurvedi 2020). Food quality can be authorized in the attitude of food items' examination concerning their microbial, fungal, and/or chemical contaminations (Noroozi & Taherian 2023). Hence, there is an urge to expand the design of quality assessment systems as technical support for quality assurance during food production.

The quality of most agricultural and food products is forcefully modified by the content of numerous physical, chemical, and microbiological agents and is actively sensitive to quality decline along all curing, processing, and storage stages. Garlic (*Allium Sativum L.*) is one of those products whose quality is strongly affected by such external factors. Due to the numerous nutritional and health benefits of this fully aromatic crop in the food and pharmaceutical industries, its cultivation and consumption are fully widespread (Mondal et al. 2022). Although the processing of garlic through new technologies can preserve the unique flavour and nutritional constituents, the storage stage is also significantly prolonged. Therefore, to enhance the quality as well as the efficiency, garlic is consumed in different ways such as fresh, dehydrated slices, powder, and tablets. The quality of garlic in each of the consumption scenarios could be affected by factors such as the presence of pathogenic contamination and/or the manner of processing.

One of the main distinct groups of pathogens invading garlic bulbs and responsible for their quality deterioration is fungi (Makarichian et al. 2022). The fungi and their secondary metabolites affect the taste of this horticultural crop by spreading undesirable aromas. This incident resulted in noteworthy threats to human health, efficiency reduction, and huge economic damages. In addition to the quality disorders, some fungi and their mycotoxins may not appear in the processed garlic in terms of appearance and may survive until the end of product processing (Gálvez & Palmero 2021). In this regard, investigation of the effect of the type of processing on the presence of infection has paramount importance.

Recently, to help better the administration of the hazardous impacts of fungal pathogens, the quality assessment approaches have been taken into consideration. The traditional approaches include the visual examination method (Dowlati et al. 2012), tissue blot immunoassay (Zia-Ul-Hussnain et al. 2013), polymerase chain reaction (De Medici et al. 2015), isozyme analysis (Yousaf et al. 2017), dot immunobinding assay (Majumder & Johari 2018), culturing and plating method (Porcellato et al. 2018), serologically specific electron microscopy (Richert-Pöggeler et al. 2019), enzyme-linked immunosorbent assay (Batrinou et al. 2020), and radio-immunosorbent assay (Kgang et al. 2023). Contrasted, the advanced approaches comprise electrochemical biosensors (Karimi-Maleh et al. 2020), volatile biosensors (Jiang & Liu 2020), optical biosensors (Meira et al. 2023), mass-sensitive biosensors (Nolan et al. 2021), and nanomaterial biosensors (Gupta et al. 2021). Despite the diverse accuracy and performance in identifying fungal pathogens infection, each of these approaches has different advantages and disadvantages. Besides the time-consuming and inappropriate for online utilization, these approaches claim well-educated instructors and large financial resources.

The aroma of processed foodstuffs like garlic could easily be varied by different factors such as type of processing (Makarichian et al. 2021), pathogen infection (Feng et al. 2022), and storage circumstances (Trindler et al. 2022). Recently, one of the favourite and easiest methods in quality assessment of foodstuffs is to check their volatile organic compounds (VOCs). Numerous investigations have been done about VOCs evaluation by conventional techniques like gas chromatography (Putri et al. 2022), gas chromatography–mass spectrometry (Hussain et al. 2023), headspace-solid phase micro-extraction (Xie et al. 2022), high-performance liquid chromatography (Zareshahrabadi et al. 2020), and electronic nose (E-Nose) (Lu et al. 2022).

Among the mentioned techniques, the E-Nose represents a further solution for online, rapid, easy, low-cost, and applied assessment of the quality of the foodstuffs (Makarichian et al. 2021). E-Nose has brought many benefits to food production industries, namely production monitoring (Calvini & Pigani 2022), quality classification (Zhang et al. 2022), product traceability (Yu et al. 2022), pathogenic detection (Das & Mishra 2022), spoilage estimation (Luo et al. 2023), and shelf-life evaluation (Singh & Gaur 2023).

Reviewing the literature exposes numerous investigations on the typical quality assessment by comparing the aroma profiles of various fresh and processed products. Nevertheless, no research has evaluated the impact of some significant treatments such as type of processing (TP), type of fungal infection (TFI), and time elapsed since the date of inoculation (TEI) on the VOC fingerprints of processed garlic as a crucial quality index. Conforming to the information prepared, there is an urge to aim on the identification of the simple and mutual influence of three critical treatments of TP, TFI, and TEI which can cause changes in physiochemical changes as well as the VOC profiles of processed garlic. Overall, the novelty of this study was to expose the feasibility of E-Nose utilization in complementary assessing the quality of contaminated garlic influenced by different processing scenarios.

Methods

Sample preparation

The garlic cloves were provided directly from a farm and detached by hand carefully. The initial moisture content of the bulbs was 3.04 ($kg_{water}.kg_{dry\ matter}^{-1}$, d.b.) which was determined based on the AOAC method at 105 ± 1°C for 24 h (Zhou et al. 2021). After careful inspection, the selected bulbs were similar in size and shape in such a way that they were immune to any decay, stain, and damage. To govern the occurrence of moisture loss, respiration, sprouting, germination, and mold growth, the bulbs were promptly sealed in low-density polyethylene (LDPE) bags and then were kept in ambient circumstances at 28 ± 1°C and ≈35% relative humidity (RH).

Inoculation

The inoculations were carried out in a sterile lab in the plant pathology laboratory, Department of Plant Protection, Faculty of Agriculture, Bu-Ali Sina University, Hamedan, Iran. 75% ethanol solution was used to sterilize the cloves' surfaces. Afterward, they were rinsed three times in sterile distilled water. To accomplish inoculation, two pathogenic fungi, namely *Botrytis allii* (BA) and *Fusarium oxysporum f. sp. Cepae* (FO) were adopted. The fungi were grown on potato dextrose agar (PDA) at 22 °C, 80% RH, and incubated for 168 h before the inoculation. Garlic was dipped for 30 s in fungal pathogens' spore suspensions (1×106 spores.mL^{-1}) (Fuentes et al. 2013; Makarichian et al. 2022; PalmEro et al. 2012). Furthermore, the non-infected samples (UIS) just immersed in sterile distilled water for 30 s. Subsequently, LDPE bags were used to store 80 samples related to each level of TFI treatment at ambient temperature for 8 days in the post-harvest technologies laboratory of the Department of Biosystems Engineering, Faculty of Agriculture, Bu-Ali Sina University, Hamedan, Iran (PHT-Lab). E-Nose measurements were performed on days 0 (D#0), 4 (D#4), and 8 (D#8) for each TP × TFI treatment combination. The olfactometery tests for D#0 were conducted up to 6 h after inoculation.

Pathogenicity quantification

Many factors affect the quality degradation of food, such as textural changes, pathogenic growths, physical damages, unfavourable storage conditions, etc. Among the mentioned cases, one of the most important situations is pathogenic growth and tissue damage. It is possible to quantitatively evaluate the quality degradation of foodstuff due to pathogenic infection (Ali et al. 2020). In this regard, the index of deterioration toughness (IDT) was estimated as an elementary quantitative method in quality assessment. A panel of 8 well-trained panellists was used to visually inspect the garlic and to rate the IDT for each level of TFI treatment based on the method utilized in previous research (Makarichian et al. 2022). Deterioration indications were classified into three groups, viz. without any degradation (G1); surface covering < 25% or inferior decay (G2); and surface covering ≥ 25% or superior decay (G3) (Eq. 1).

$$\mathrm{IDT} = \frac{(0 \times \mathrm{N_{G1}}) + (1 \times \mathrm{N_{G2}}) + (2 \times \mathrm{N_{G3}})}{2\mathrm{n}} \times 100 \tag{1}$$

Where IDT is the decay severity index (%), n is the quantity of visually inspected garlic, and N_{G1}, N_{G2}, and N_{G3} are the respective numbers of garlic for each group associated with the toughness of deterioration.

Processing procedure

In this research, four levels of processing treatment were employed i.e. unprocessed whole garlic (UW) as the control level, dried sliced garlic (DS), garlic powder (PO), and garlic tablets (TA) which are depicted in Fig. 1.

Drying

The flaked-off garlic was sliced manually into 2–3 mm thicknesses. The slices were dried by a near-infrared vacuum drying which was established in the PHT-Lab (Fig. 2). The structure and performance of the applied drier as well as the dehydrating process have been reported in the previous research (Makarichian et al. 2021). Three replications of drying experiments were conducted at 60 °C and 20 kPa of vacuum pressure (Lilia et al. 2017). Dehydration was prolonged until the moisture content of 0.06 ($kg_{water}.kg_{dry\ matter}^{-1}$, d.b.) was achieved. On each day of the experiment, the initial moisture content of the samples was determined again. The initial moisture of the samples associated with D#0, D#4, and D#8 were 3.04, 2.69, and 2.44 ($kg_{water}.kg_{dry\ matter}^{-1}$, d.b.), respectively.

Powdering

The DS samples were ground and crushed for 60 s by a grinder (MJ-M176P, Panasonic Manufacturing, Berhad, Malaysia). To homogenize the particle size, the resulting ground garlic powder was sieved with a 40-mesh sieve. The remaining particles in the sieve were ground again in such a way that the particle size of the garlic powder material applied for tableting was less than 0.4 mm (Fig. 1).

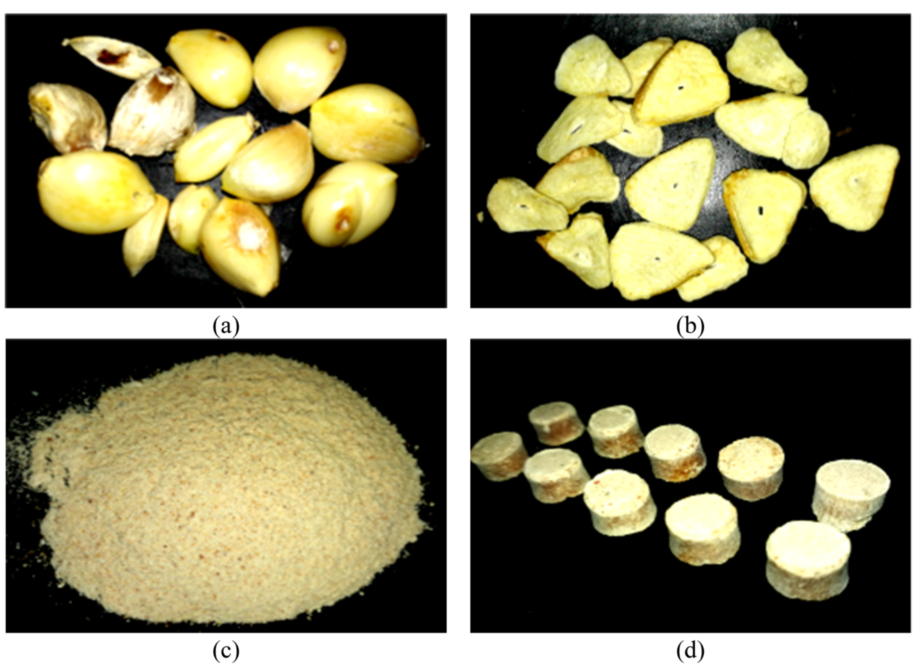


Fig. 1 The levels of TP treatment: (**a**) unprocessed whole garlic (UW), (**b**) dried sliced garlic (DS), (**c**) garlic powder (PO), and (**d**) garlic tablets (TA)

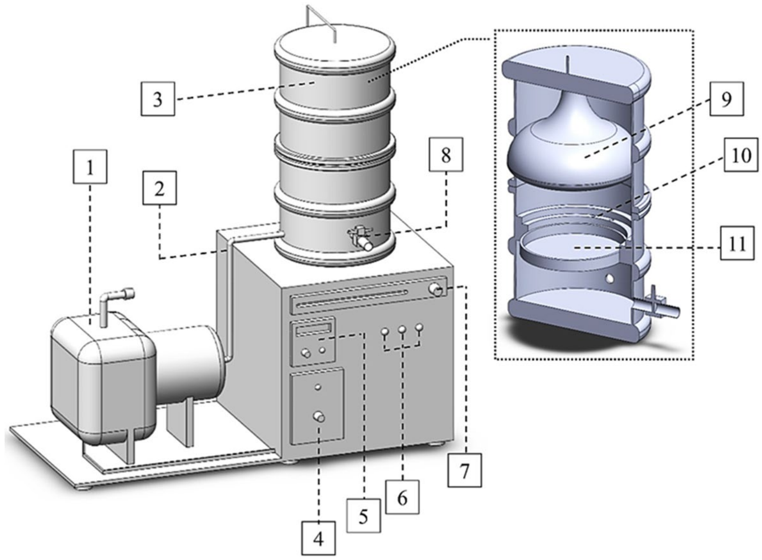


Fig. 2 Schematic view of utilized dryer: 1. Vacuum pump, 2. Vacuum hose, 3. Drying chamber, 4. Dimmer, 5.Thermostat, 6. Signal indicators, 7. Absolute pressure stabilizer, 8. Breaker vacuum valve, 9. Tungsten lamp, 10.Temperature and pressure sensors, 11. Sample tray

Tableting

To produce garlic tablets, a lab-scale hydraulic press machine (Fig. 3) and a closed mould were used which were designed and fabricated in the PHT-Lab (Ghasemi & Chayjan 2019). The utilized mould included an upper jaw, a lower jaw, a small middle mould (matrix), a piston, and a mandrel (Fig. 4). The matrix was placed between the upper and lower jaws. This small mould had a round cross-section and a hollow hole. The diameter of the matrix hole determined the diameter of the final tablet.

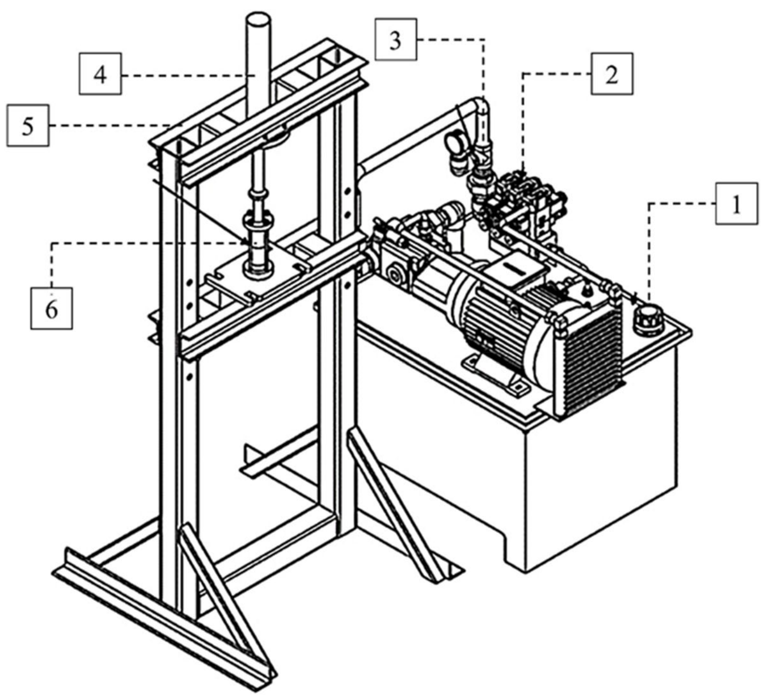


Fig. 3 Lab-scale hydraulic press machine: 1. Power pack, 2. Flow control valve, 3. Pressure control valve, 4. Hydraulic jack, 5. Chassis, 6. Mould (Ghasemi & Chayjan 2019)

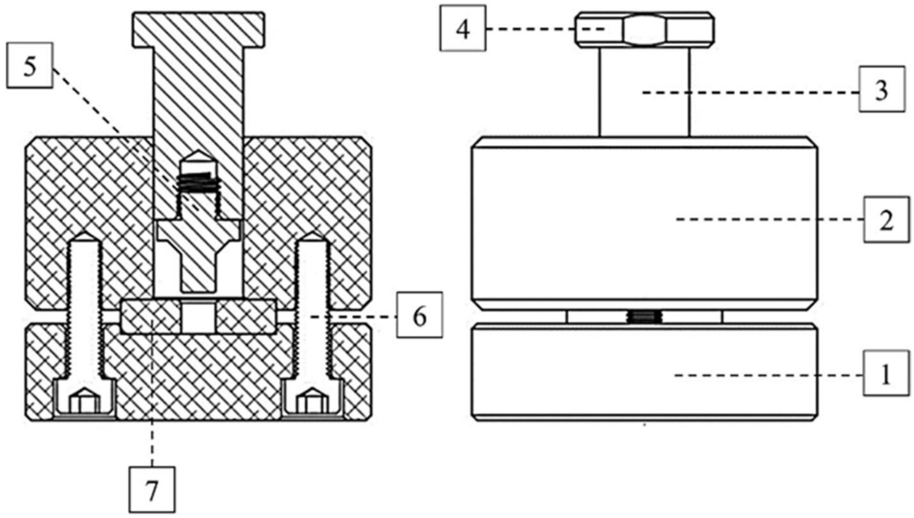


Fig. 4 The utilized mould: 1. Lower jaw, 2. Upper jaw, 3. Piston, 4. The location of force application on the piston, 5. Mandrel, 6. Guide screws, and 7. Matrix

Hence, to produce garlic tablets with different diameters, it was possible to use matrices of different diameters. To apply pressure in the tableting step, it was possible to use mandrels with different diameters which are attached to the piston.

The tablet diameter, loading speed, and hydraulic pressure were adjusted as 10 mm, 2 mm.s^{-1}, and 100 bar, in order of appearance. During tableting, the material is pressed into the mould by the jack, and when the applied pressure reaches the desired level, the piston stays motionless on the material for 30 s to make the tablets relax. Subsequently, the two jaws were slowly detached and the compressed tablet was taken out of the mould.

E-Nose analyses

The machine olfactory was designed and fabricated in the PHT-Lab. The characteristics and the functioning of the utilized E-Nose in this research have been fully described in previous research (Makarichian et al. 2021, 2022). The olfactory experiments included three main steps, i.e. baseline correction, headspace injection, and sensor recovery. To compensate for the drifts as well as enhance the precision, the baseline correction step was applied. Subsequently, as the headspace injection took place, the chemical fluctuations transformed into electrical signals by MOS sensors. This step was continued until the sensors' reactions toward the presence of VOCs were neutralized. In the sensor recovery step, the operational surfaces of sensors must be cleaned of any aromatic contamination to avoid errors in sensor functions associated with the following olfactory experiments.

The optimal duration of each step was achieved by trial and error. To enhance the precision of data analyses, olfactory tests were directed in $\geq S+1$ replications, where S is the number of variables (MOS sensors). To improve the sensors' precision, the data related to the headspace injection step were pre-processed by fractional method before analyses and classification (Eq. 2). The application of this approach resulted in a normalized and dimensionless response for each sensor (Heidarbeigi et al. 2015):

$$R_{PP}(t) = \frac{R_D(t) - R_{BL}}{R_{BL}} \quad (2)$$

Where $R_{pp}(t)$, $R_D(t)$, and R_{BL} are pre-processed response, dynamic response, and baseline value, in the order of appearance.

Statistical data analyses

The data acquired by the E-Nose were analysed by the PCA, LDA, SVM, and BPNN. The PCA is a dimensionality reduction technique that is frequently employed for large data sets in such a way that still covers most of the information related to the primary sets. The LDA is one of the most common approaches in the applications of pattern classification. To keep away from the adversity of dimensionality, the LDA as a supervised classification technique, aims to map the features in higher dimensional space onto a lower dimensional. The SVM is a supervised learning model with supplementary learning algorithms for the classification application. Compared to other algorithms of classification, this technique is faster and has more reliable performance with limited-size data sets. The BPNN model is a supervised model that assumes an error-reverse algorithm. The BPNN brings about a convergence of the results to the predictable value based on adjustment of the weights and other considerations throughout training. The PCA, LDA, and SVM were conducted using The unscrambler X 10.4 (CAMO ASA, Norway), while the BPNN was employed via the Matlab R2015b (The Mathworks Inc., Natick, MA, USA).

Results and discussions

Pathogenicity quantification

The decay caused by the presence of infection was identified at all levels of the TFI treatment. The results are depicted in Fig. 5. As the TEI treatment progressed, the IDT increased exponentially. The rate of tissue degradation of all samples between days D#4 and D#8 was considerably higher than the rate that belonged to the interval of days D#0 and D#4. The reason for this point was the growth of mycotoxins and the production of secondary metabolites, which progressively affected and deteriorated the garlic tissue. According to previous research, the best time to detect fungal contamination is eight days after garlic has been inoculated into fungal pathogens. Consequently, the levels of TEI treatment in this study were considered only up to the 8th day (Makarichian et al. 2022).

Early signs of corruption in infected samples were observed from day D#4, while there were signs of apparent degradation of tissue in the UIS samples on day D#8. The results of IDT revealed that throughout the monitoring period, the least changes in appearance quality and tissue degradation were observed in the UIS samples, while the most changes were related to the BA-infected samples. At the end of the monitoring period (D#8), the IDT of UIS, FO-infected, and BA-infected samples were 6.875%, 30%, and 48.125%, in the order of appearance.

These results disclosed the concept that the rate of decay in foodstuff is significantly influenced by external factors such as the presence of fungal contamination (Payuhamaytakul et al. 2019). Wu et al. (2023) stated that the greatest loss of citrus occurred when the product was infected with fungi. They specified that the type of fungal infection also affects the rate of citrus decay as well as the manner of its degradation. Bartholomew et al. (2021) also emphasized that identification of fungi and clarifying the early signs of fungal contamination are important in reducing food waste and maintaining its quality.

Sensors' array responses

The responses of the sensor array toward the garlic's aroma in all levels of TP treatment are depicted in Fig. 6. The results indicated that the sensitivity of the sensor array was different for each level of TP treatment. The most changes in the response of the sensors were related to the UW level, while the lowest range of excitation was observed toward the TA level. In other words, employing different processing steps led to a reduction in garlic's

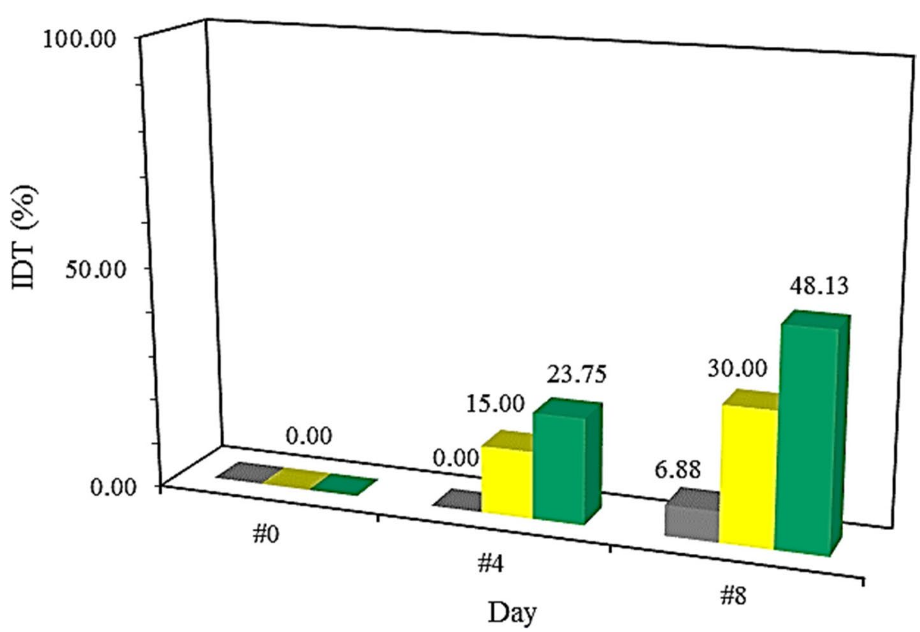


Fig. 5 Index of deterioration toughness (IDT) of garlic associated with the different levels of processing treatment during 8 days after inoculation: non-infected samples (UIS), *Fusarium* infected samples (FO), *Botrytis* infected samples (BA)

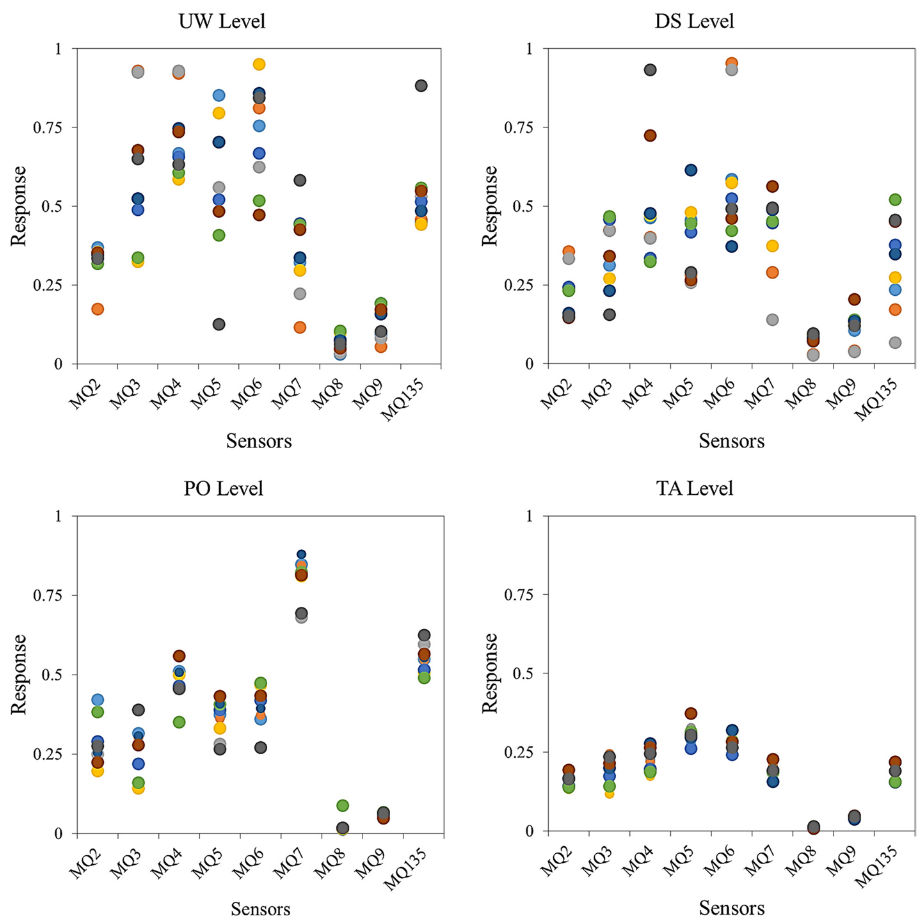


Fig. 6 Normalized responses of sensors' array toward the aromas related to the different levels of TP treatment in interaction of TFI × TEI combination treatments; UIS*D#0, UIS*D#4, UIS*D#8, BA*D#0, BA*D#4, BA*D#8, FO*D#0, FO*D#4, and FO*D#8

aroma emission compared to the control level of TP treatment (UW). In olfactometery experiments related to the UW level, the MQ5 and MQ8 had the highest and lowest range of excitation, respectively. Besides, the lowest and highest changes in the response of the sensors array toward the aroma of DS level were detected in MQ8 and MQ4 sensors, respectively. In the next levels of TP treatment viz. the PO and TA levels, the lowest and highest range of sensors stimulation belonged to the MQ9 and MQ3 sensors, respectively. These results clarified that the processing of the product as well as its type can easily alter the aroma of garlic (Fig. 6). Hence, the ideal implementation of product processing should be in a manner that the quality and appearance of the product (such as its aroma) does not change undesirably.

Although each level of TP treatment caused changes in the aroma diffusion, the presence of fungal infection led to robustness in aroma diffusivity. The reason was the damage caused by fungal pathogens to the garlic's tissue. As the reaction of the sensors' array proved, the effect of fungal infection on the garlic's aroma in the levels of UW and DS was greater than at other levels. The reason for this point could be the existence of some courses such as heating (in dehydration), grinding (in powdering), and intense compression (in tableting) which induced fading of the damages resulting from fungal pathogenic invasion.

As the levels of TP treatment progressed, the effective diffusivity of aroma declined. Hence, the aroma was emitted by lower resolution which resulted in the blurring of the influences related to the presence of fungal contamination. In this regard, the pathogenic contaminations may not be recognizable even in terms of quality's appearance. This means an increased risk of unintentional consumption of contaminated processed garlic. Therefore, the quality assessment as well as health monitoring in foodstuff processing is crucial and should be done at the earliest stages of that.

The response of the array demonstrated that the aromas' garlic altered versus the different levels of TEI treatment. In UIS samples, the sensor stimulus decreased from D#0 to D#8, while these changes had an ascending-descending trend in infected samples. The lowest and highest range of sensor stimulus toward the aroma of infected samples were on the D#0 and D#4, in the order of appearance. The reason was that the fungal infection resulted in structural and tissue damage which facilitated the severe diffusivity of the unpleasant aroma of garlic. Noteworthy, in the olfactometery of BA-infected samples, the level of stimulus in the array was more widespread rather than in the FO-infected samples and the reason was the more destructive effects caused by BA fungus.

The literature exposed that treatments like TP, TFI, and TEI cause changes in the aroma of garlic products (Chen et al. 2019; L. Jiang et al. 2023). De Melo Pereira et al. (2019), evaluated the green coffee's aroma alteration through postharvest processing. The results indicated that the volatile constituents of the final product of coffee beans could be affected by postharvest processing including drying and storage processes. Labanska et al. (2022), assessed the onions contaminated with *Fusarium* fungi. Their results demonstrated that the physiochemical changes in the samples related to the development of the disease could alter the aroma of foodstuffs.

PCA results

The results of PCA method utilization in the multivariate interpretation of the array's response associated with samples' olfactometery revealed that the garlic's aroma was actively touched by the TP treatment. The results exposed that PC-1 and PC-2 labelled 40% and 18% of the data, respectively. According to Fig. 7-a, it was instituted that the scores associated with UW samples were on the

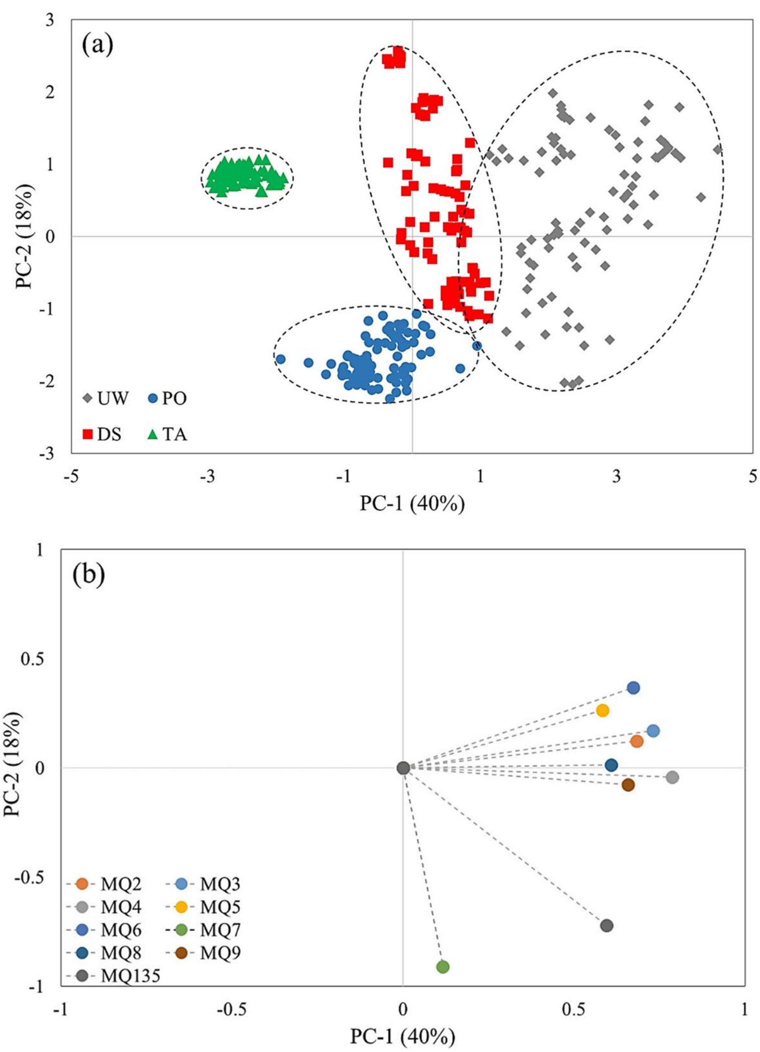


Fig. 7 The results of PCA employment in the multivariate analysis of samples' aroma related to different levels of TP treatment: (**a**) Scores plot, (**b**) Loading values plot

right side of the PC-1 axis, whilst the scores associated with TA samples were on the left side. As the different levels of TP treatment were applied, the dispersion of the score values related to each level decreased. In other words, the influence of TFI as well as TEI treatments on the aroma became more limited. Remarkably, there was a slight overlap between the scores associated with UW, DS, and PO samples. To obtain more clarity about the influence of TFI and TEI treatments, the results of olfactometery tests related to each level of TP treatment were done separately. Moreover, the loading values of the sensors array demonstrated that all sensors apart from sensors MQ5, MQ7, and MQ135, had a significant effect on the positioning of score values along the PC-1 axis, while the most effective sensors in the arrangement of scores along the PC-2 axis were MQ135 and MQ7, in the order of appearance (Fig. 7-b).

The results of PCA utilization in the multivariate investigation of the data obtained by olfactometery of UW samples (Fig. 8-a) revealed that the presence of infection as well as the application of different levels of TFI treatment outset the score values to decrease in the direction of the PC-1 axis. In this analysis which a total amount of 55% of the data was described, there was an insignificant overlap between the score values associated with UIS and FO-infected samples. This overlap was related to the aroma of UIS*D#4 and UIS*D#8 treatment combinations, which extend over the scores' pattern of FO*D#4 samples. It should be mentioned that the application of TEI treatment which resulted in the progression of fungal infection caused further tissue destruction. This ruination led to significant changes in the score values along the PC-2 axis (Fig. 8-a). In UIS samples, there was an overlap between the patterns of score values related to

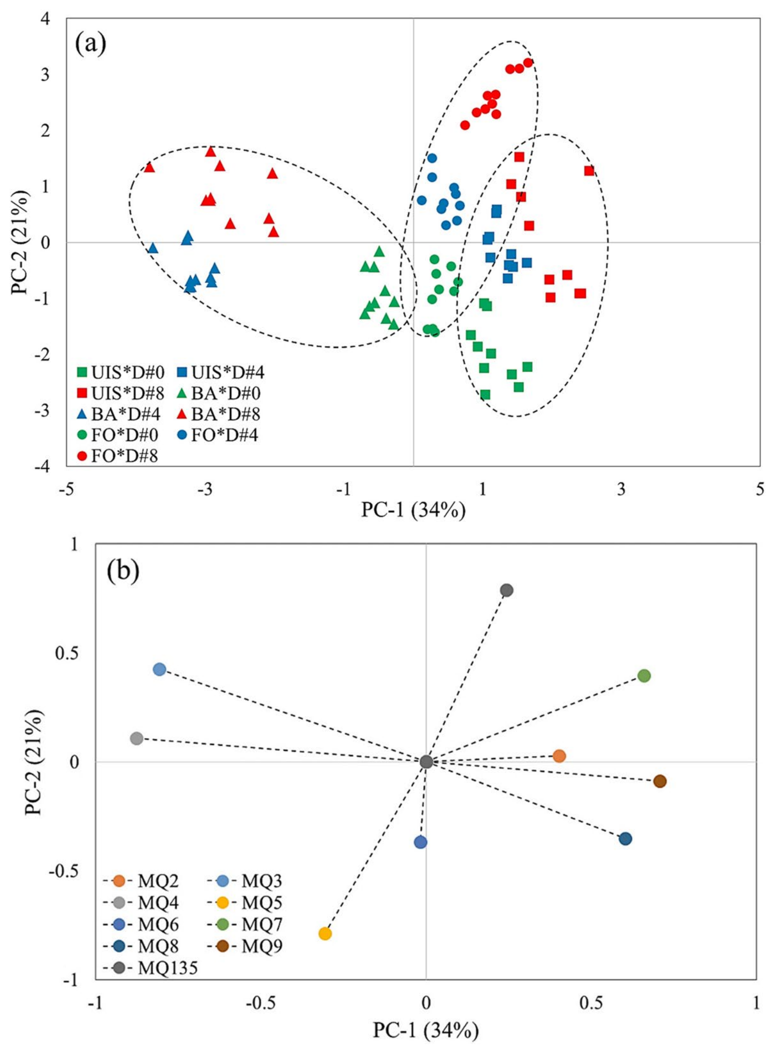


Fig. 8 The results of PCA employment in the multivariate analysis of samples' aroma related to unprocessed whole samples (UW): (**a**) Scores plot, (**b**) Loading values plot

the UIS*D#4 and UIS*D#8 samples, whilst in the infected samples there was no overlap in any levels of the TEI treatment.

According to the loading values of the sensors array (Fig. 8-b), it was also found that MQ7 and MQ9 had the most effect on the arrangement of score values in the positive direction of the PC-1, while MQ3 and MQ4 had the most effect on the positioning of these values in the negative direction. It has also appeared that the MQ135 and MQ5 had the greatest effect on the placement of score values in the positive and negative direction of the PC-2 axis, respectively. Therefore, the MQ3, MQ4, MQ7, and MQ9 had significant stimulation toward the TFI treatment, whilst the MQ5 and MQ135 had the most sensitivity in contact with the TEI treatment (Fig. 8-b).

In the analysis of the data obtained by the olfactometery tests of DS samples, the PCA described 58% and 17% of data in the PC-1 and PC-2, respectively (Fig. 9-a). Although the score values associated with all DS samples had convergence on the D#0, the application of the following levels of TEI treatment led to an increase in the dispersion of the score values. This point is caused by pathogenic degradation. In other words, the TFI treatment exhibited its effectiveness along the PC-1, while the dispersion of score values along the PC-2 was generated by the application of the TEI treatment.

On D#0, there was a slight overlap between the patterns of score values related to the UIS*D#0 and BA*D#0 treatment combinations of DS samples, whilst no overlap was seen in the rest of the combinations. Although it was possible to detect fungal infection of DS samples easily, there were challenges in recognizing the type of pathogens. According to the high IDT of BA fungus, there was a big gap between the patterns of D#0

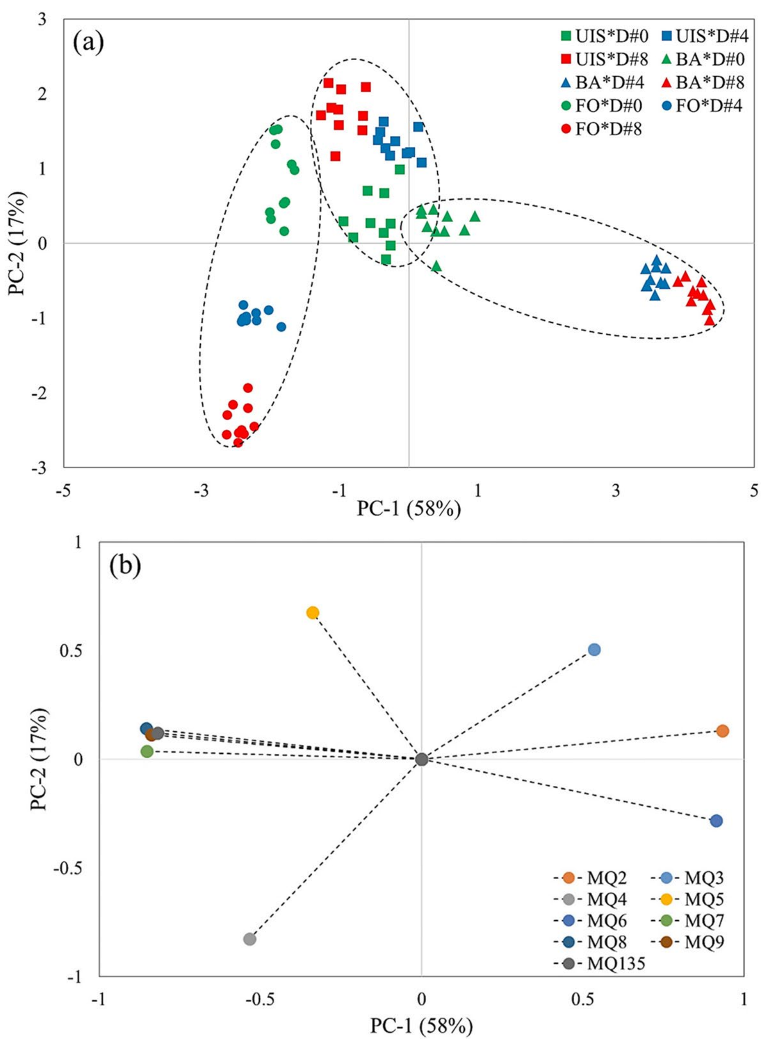


Fig. 9 The results of PCA employment in the multivariate analysis of samples' aroma related to dried slices samples (DS): (**a**) Scores plot, (**b**) Loading values plot

and the set of D#4 and D#8. The loading values of the sensors of E-Nose also depicted that except for MQ3, MQ4, and MQ5, the rest of them had a significant role in the positioning of scores along the PC-1 axis. In other words, they were advantageous in investigating the effect of applying different treatments on the aroma of the DS sample. In contrast, the MQ4 and MQ5 had a significant effect on the positioning of scores along the PC-2 (Fig. 9-b).

The results of PCA in multivariate analysis of the data obtained by garlic PO olfactometery tests revealed that 47% of the total data related to different TFI × TEI combinations were specified. The aroma of all combinations related to PO samples could not be distinguished until the D#4. Conversely, the patterns associated with the aroma of the infected samples were recognizable from the UIS ones in D#8. As with the previous levels of TP treatment (UW and DS), the TFI had a superior effect than the TEI in the PO's aroma alteration (Fig. 10-a).

The loading values associated with the sensors also depicted that the MQ3, MQ135, and MQ6 in the order of appearance had the greatest weight in the positioning of scores along PC-1, i.e. they had the most stimulus toward the different levels of TFI treatment. However, only the MQ9 had significant responsiveness versus the arrangement of scores along the PC-2 as well as the TEI levels variation. Although MQ8 and MQ9 did not have a significant level of stimulation, the range of changes in their response was impressive in the evaluation of the aromas related to the different treatment combinations (Fig. 10-b).

The results of PCA in the analysis of the data acquired from the olfactometery experiments of TA samples indicated that PC-1 and PC-2 included 35% and 20% of the

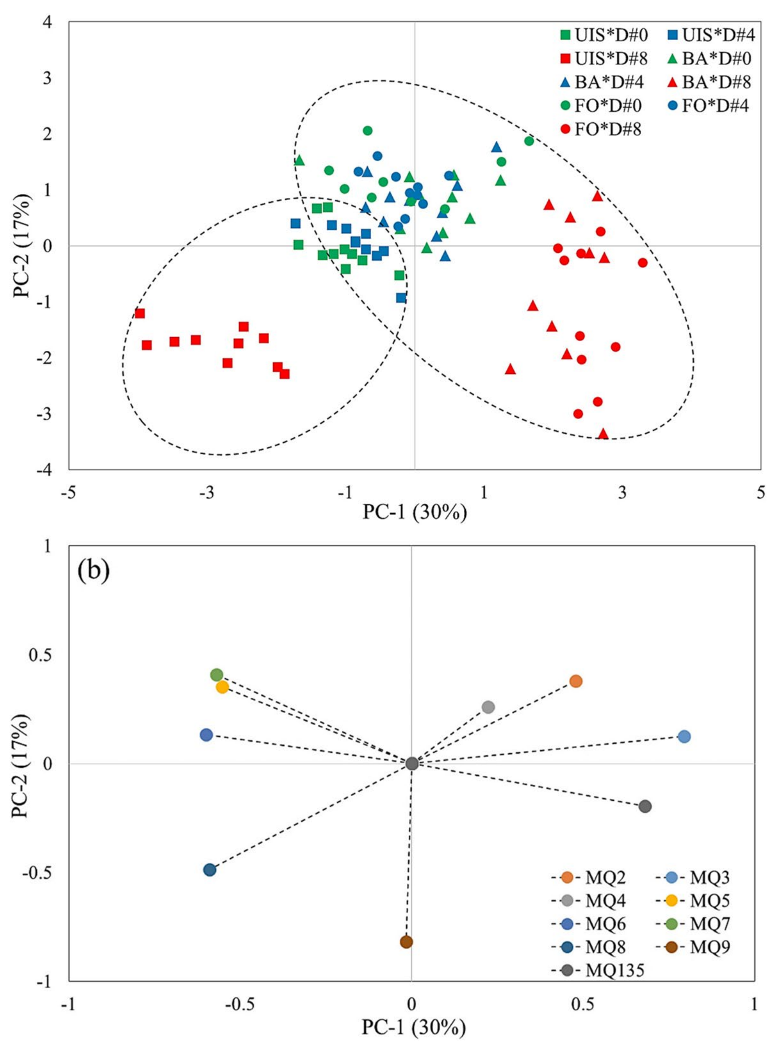


Fig. 10 The results of PCA employment in the multivariate analysis of samples' aroma related to garlic powder (PO): (**a**) Scores plot, (**b**) Loading values plot

obtained data, respectively (Fig. 11-a). The pattern of score values related to TA samples was such that it was not achievable to differentiate the aroma of all treatment combinations. In other words, it was not possible to keep apart the patterns based on the TFI and TEI treatments.

Generally, the consequence of the PCA disclosed that the TP treatment had considerable influences on the severity of spreading spoilage caused by fungal infection and, as a result, the aroma of samples. Literally, in the case of UW and DS samples, the influence of TFI and TEI treatments; in the case of PO samples, only the influence of TFI treatment; and in the case of TA samples, the influence related to none of the mentioned treatments were assessable. These outcomes did not mean that the application of different levels of TP treatment eliminates the effects of fungal infection or the decay caused by it. On the contrary, the detection of aroma alteration based on the TFI and TEI treatments could not be possible in the final levels of TP treatment, due to aspects such as severe deterioration of garlic's tissue; increasing the internal surface effective in aroma diffusion; and maximum mixing of un- and infected samples related to each treatment combination as much as possible. Demirok and Yıkmış (2022), stated that different processing methods can affect the quality conditions of the product such as bioactive compounds, amino acids, mineral compounds, and also the growth conditions of pathogens.

Classification results

The results of the PCA method revealed that the effect of TP treatments can overshadow the effects of TFI treatment. Subsequently, by the employment of some classifier methods such as LDA, SVM, and BPNN, the aroma of garlic was categorized to deduce how much it can be

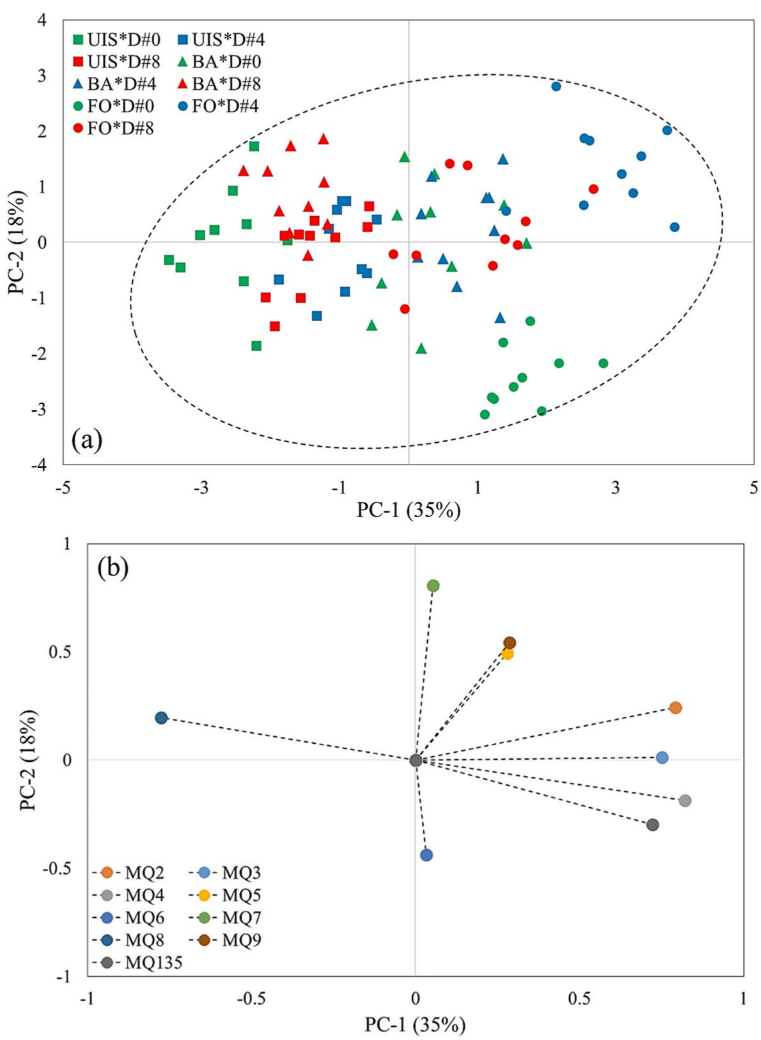


Fig. 11 The results of PCA employment in the multivariate analysis of samples' aroma related to garlic tablets (TA): (**a**) Scores plot, (**b**) Loading values plot

practically considered as a qualitative parameter in product health monitoring. The dataset employed for all classifiers was consistent with the one utilized for PCA. In LDA and SVM methods, the default setting took on identical prior probabilities for class membership. Besides, the standard backpropagation algorithm of artificial neural networks was employed in BPNN. The network structure was selected in such a way that the sensor array responses and the levels of the TFI and TEI treatments were considered as the input and output vectors, respectively. The number of neurons in the hidden layer was also considered as 10 by default. Thus, the network topology became 9*10*3. Noteworthy, the dataset employed in BPNN was randomly categorized into the training (60%), test (20%), and verification sets (20%).

The classification of the UW samples' aroma based on TFI treatment by the LDA method disclosed that 90% of the samples were classified correctly. At the level of UW, the LDA distinguished the infected samples more than the non-infected ones. Precisely, the LDA correctly classified infected and non-infected samples related to the treatment level of UW with an accuracy of 97% and 86%, respectively. In the classification of UW samples based on the TFI treatment, the SVM method was less accurate than the LDA method, in such a way that almost 72% of all samples were classified correctly. Unlike the LDA method, the SVM was able to classify the non-infected UW samples better than the infected ones. The employment of the BPNN method led to a completely correct classification of UW samples based on the different levels of TFI treatment (Table 1).

In the classification of aromas associated with UW samples based on the TEI treatment, it was also perceived that the best result was related to the BPNN procedure with an accuracy of 90%. The LDA method was able to better distinguish the aroma of UW samples on days D#0 and D#8. As the different levels of TEI treatment progressed, the destruction of garlic tissue increased. This was the reason for the touchable differentiation of the aroma from the beginning of the monitoring period to its end. Besides, the employment of TEI's different levels coincided with the decrease in the SVM classification accuracy, so the lowest and highest accuracy of classification was achieved on days D#8 and D#0, respectively. The reason for the difference in the accuracy of the LDA and SVM methods could be described in the fact that the SVM method uses a binary mode in classification, whilst the LDA classifies linearly and points out the difference between the classes more clearly. The BPNN method also accomplished the classification same as the LDA. Although the LDA classified the aroma of UW samples more accurately in the levels of D#0 and D#8, the accuracy of BPNN was higher (Table 1).

In the aroma classification of DS samples of garlic based on the TFI treatment, the highest and lowest classification accuracy was observed in BPNN and SVM methods, in the order of appearance. All classifiers were able to fully recognize the aroma of non-infected DS, while there were misclassifications in infected categorization. As a reason, it can be pointed out that the presence of fungal infection was affected by thermal processes so the aromas of infected and non-infected samples were merged more than the previous level of TP treatment.

In the classification of the aroma of DS samples based on the TEI, the LDA, SVM, and BPNN methods had an accuracy of 91.11%, 62.22%, and 96.5%, in order of appearance. The LDA and BPNN methods classified the DS samples more accurately on days D#0 and D#8. On day D#4, the misclassified samples were wrongly placed in the category of D#8. In other words, this point indicated that the DS samples started to spoil before D#4. It should be mentioned that the rate of degradation of the samples between D#0 and D#4 was higher than the same case in D#4 and D#8. In the classification of the aromas

Table 1 The accuracy of LDA, SVM, and BPNN methods employed to classify the aroma of garlic in different processing steps and based on TFI and TEI treatments

Processing step	Classification basis	LDA (%)	SVM (%)	BPNN (%)
Unprocessed whole garlic (UW)	TFI[a]	90.00	72.22	100.00
	TEI[b]	84.44	67.78	90.00
Dried slices of garlic (DS)	TFI	93.33	80.00	97.80
	TEI	91.11	62.22	95.60
Garlic Powder (PO)	TFI	88.89	75.55	92.20
	TEI	70.00	53.33	72.20
Garlic tablet (TA)	TFI	60.00	40.00	77.78
	TEI	80.00	44.44	82.20

[a] TFI: Type of fungal infection

[b] TEI: The time elapsed since the date of inoculation

related to the DS samples based on the TEI, the SVM method had errors in all levels, particularly on D#4 and D#8. The lowest and highest accuracy in the SVM classification of DS' aroma based on the TEI were obtained on D#0 (90%) and D#8 (≈33%), respectively (Table 1).

In the classification of aromas regarded to PO samples based on the TFI treatment, the highest and lowest accuracy were perceived in BPNN (92.2%) and SVM (75.5%) methods, in the order of appearance. Although the aroma of non-infected PO was classified with the highest accuracy in LDA and SVM methods, there were many misclassifications in infected ones. Incompatible with these two remarked methods, the BA-infected samples were categorized with an accuracy of 100% in the BPNN method, while there were disarranged classifications in aromas related to UIS and FO-infected samples. Although the outcomes of the BPNN method were better, the results of the LDA and SVM approaches were more rational (Table 1).

In classifying TA's aromas based on the TFI treatment, the LDA, SVM, and BPNN methods had an accuracy of 60%, 40%, and 77.78%, in the order of appearance. All classifiers were able to categorize the UIS aromas with the highest exactness. As a reason, the mixing of samples during the powdering as well as the presence of condensation during the tableting caused the aroma convergence of the infected samples. Moreover, this similarity of the infected samples' aroma had a significant differentiation from the aroma of non-infected samples, whose tissues were less degraded (Table 1).

The classification of TA's aroma based on the TEI treatment also revealed that the highest accuracy was obtained in the BPNN method (82.2%), while the lowest accuracy was noticed in the SVM method (44.44%). In all classifiers, the highest correct grouping was achieved on D#8, while the most misclassification was documented on D#0 and D#4, respectively. It can be concluded that tissue degradation and change of structure caused by powdering and tableting could overshadow the rate of aroma changes on D#0 and D#4. Tissue degradation and consequently aroma changes on the D#8 were such that the aroma related to this level of TEI treatment was dissimilar to other days and the processing could not make an impact on the aroma. Therefore, it is necessary to mention that in quality monitoring of processed products, the aroma can play a key role as a qualitative indicator (Table 1).

Generally, it should be noted that as the processing steps progressed, the aroma of the garlic products underwent more transformation, so the accuracy of aroma classification decreased. It was found that the aroma classification of all samples based on the TFI Treatment was more accurate than the TEI treatment. Because the influence of fungal contamination on the aroma alteration at each step of processing is much greater than the duration of infection. Yan et al. (2021), noted the key role of fungal contamination on the aroma of tea products and during processing. They stated that aromatic changes due to fungal infection have a significant effect on the essence and physical characteristics of processed tea. Gao et al. (2021), announced that during the storage period and by applying different processing steps, the VOCs of rice altered. Therefore, changes in aroma can be used as a comprehensive factor in the quality control of processed products.

Conclusions

To investigate the reciprocal effects of different processing methods and fungal contamination, the garlic's aroma was evaluated using an E-Nose. The results demonstrated that the decay caused by fungal infection was identified at all levels of the TFI treatment. As the different levels of TEI treatment were employed, the IDT increased. The results indicated that the response of the array was inconsistent with each processing step. Although applying different levels of TP treatment reduced the aroma diffusion of garlic, the presence of fungal infection increased the emission of that. According to the E-Nose results, the aromas of garlic altered versus the different levels of TEI treatment. The results of the PCA method revealed that the garlic's aroma was actively touched by the TP treatment. The PCA results exposed that in the case of UW and DS samples, the influence of TFI and TEI treatments; in the case of PO samples, only the influence of TFI treatment; and in the case of TA samples, the influence related to none of the mentioned treatments were assessable. The consequences of classifiers revealed that as the processing steps progressed, the aroma of the garlic products transformed more so the accuracy of aroma classification was reduced. The classifiers outcomes evidenced that the aroma classification of all samples based on TFI treatment was more accurate than TEI treatment. The results of the study of aroma as a qualitative characteristic exposed that the two concepts of processing and pathogenic contamination can overshadow each other's effects and ultimately alter the quality of foodstuffs such as garlic.

Acknowledgements

The authors would like to thank the Bu-Ali Sina University for financial support.

Authors' contributions

AM, RAC and EA were involved in the study conceptualisation and writing of the original manuscript draft, developing data collection tools, data collection. SSM and DZ were responsible for experiments. All the authors were involved in reviewing and editing, and approving the final manuscript.

Funding

This work was funded by Bu-Ali Sina University.

Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interest.

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Received: 30 October 2023 Accepted: 15 January 2024
Published online: 02 September 2024

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