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A classification based on support vector machines for monitoring avocado fruit quality

Avokado meyve kalitesinin izlenmesi için destek vektör makinelerine dayalı bir sınıflandırma

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Abstract

Scientifically, the efficiency of a method refers to its power to best predict/calculate based on an evaluation following a certain process within the current scenario, parameter and/or data. For a good prediction, the most appropriate approach(es) to a problem should be considered and the related tests should be done reliably. Practical studies in the field of food safety and fruit quality are critical, with the accuracy, speed and economic parameters of the methods used being of particular importance. In this study, for the first time in literature an Arduino-based temperature and gas monitoring system (called e-nose) is used to monitor the decay of avocado fruit in a controlled experimental environment and support vector machines, a machine learning method, are used to detect (classification) the decay. In this study, test and validation success of over 99% was achieved with very few training-data for classification. The obtained results are encouraging in terms of the detection results of the developed e-nose and the method used to determine the level of decay in other fruit in cold storage.

Keywords: Food safety, Machine learning, Support vector machines, E-nose, Fruit quality, Avocado.

Öz

Bilimsel olarak, bir yöntemin etkinliği, mevcut senaryo, parametre ve/veya veriler içinde belirli bir süreci takip eden bir değerlendirmeye dayalı olarak en iyi tahmin/hesaplama gücünü ifade eder. İyi bir tahmin için probleme en uygun yaklaşım(lar)ın göz önünde bulundurulması ve ilgili testlerin güvenilir bir şekilde yapılması gerekmektedir. Gıda güvenliği ve meyve kalitesi alanında yapılan uygulamalı çalışmalar, kullanılan yöntemlerin doğruluğu, hızı ve ekonomik parametrelerinin özellikle önemli olması ile birlikte kritik öneme sahiptir. Bu çalışmada, literatürde ilk kez, Arduino tabanlı bir sıcaklık ve gaz izleme sistemi (e-burun olarak isimlendirilir) ile kontrollü bir deney ortamında avokado meyvesinin çürümesi izlenerek verileri alınmakta ve çürümeyi tespit etmek (sınıflandırmak) için bir makine öğrenmesi yöntemi olan destek vektör makineleri kullanılmaktadır. Bu çalışmada, sınıflandırma için çok az eğitim verisi ile %99'un üzerinde test ve doğrulama başarısı elde edilmiştir. Elde edilen sonuçlar, geliştirilen e-burun tespit sonuçları ve soğuk hava deposunda diğer meyvelerdeki çürüme seviyesinin belirlenmesinde kullanılan yöntem açısından cesaret vericidir.

Anahtar kelimeler: Gıda güvenliği, Makine öğrenmesi, Destek vektör makineleri, E-burun, Meyve kalitesi, Avokado.

1 Introduction and related works

The continued rapid global population growth has led to an increase in demand for food products. Both qualitative and quantitative studies have been carried out to identify how best to address this issue, while agricultural areas have been expanded and the number of producers and carriers has been increased [1],[2]. To improve access to safe food, which is becoming harder under the strain of the growing global population, studies have been conducted into production planning and the creation of more efficient supply chains that eliminate production bottlenecks [3]. The development of technology-based methods is accelerating due to the serious problems being encountered in food production and the supply chain due to climate change, water scarcity and COVID-19 [4]-[7]. The Fourth Industrial Revolution (referred to as Industry 4.0) that emerged with the advent of nanotechnologies and the Internet of Things (IoT) has contributed to the improvement of production systems, increased production and the optimization of supply chain processes [8]-[10].

One of the main issues addressed in agricultural studies is to how best to ensure the delivery of fruit and vegetables of the highest quality to the consumer after harvesting, given the loss in both qualitative and quantitative properties during post-harvest processing, transportation and storage [11]. The main issue in this regard is the continued metabolic activity in fruit and vegetables after harvesting in the form of respiration and transpiration. The duration of storage of fruits and vegetables

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in cold storage depends on the temperature and humidity of the warehouse. Furthermore, as the respiration rate of each fruit and vegetable is different, their shelf life also differs. The increased production of ethylene as a result of metabolic activity increases the respiratory rate and reduces the shelf-life of products after harvesting, and so the optimum cold storage conditions should be provided to slow down the respiration, and thus extend the storage life of products [12]. As the ideal conditions (storage temperature and relative humidity) for each fruit or vegetable type differ, each requires its own cold storage environment [13]. As a further issue, fruit and vegetables are prone to damage during harvesting or transportation, leading to faster deterioration, and the early detection of decay is vital in ensuring the preservation of the freshness of the products. Existing automatic control systems heavily rely on human labor, whereas the proposed control system significantly reduces this requirement. Moreover, the suggested system provides enhanced accuracy and precision in comparison to other systems. This enables the early detection of decay, facilitating prompt removal and minimizing damage to surrounding products. Consequently, this approach leads to reduced waste. It has been suggested that carrying out such controls automatically rather than manually will reduce the cost of cold storage and will allow consumers to obtain fruit and vegetables at more affordable prices. On the other hand, thanks to the warning system integrated into individual refrigerators with this control system, the products are protected from decay and wastage. Although the establishment of such an autonomous structure would require a certain cost outlay, it is very low when compared to the investment costs for the installation of a controlled environment and modified atmosphere packaging systems [14].

Sustainable solutions are sought for all kinds of control processes during the planting, harvesting and storage phases of food production, to ensure food safety, extend shelf life and reduce waste [15]. For the management of such processes, methods that are based on image processing and machine learning have been shown to achieve successful results [16], [17]. An electronic nose (e-nose) system that collects data from MQ gas sensors has been designed by Caya et al. [18]. In this study, they have made classification using principal component analysis and the k-Nearest Neighbors (*k-NN*) method [18]. Similarly, an e-nose system has been developed by Sarno and Wijaya [19] for the rapid evaluation of the quality of perishable beef stored in a refrigerator, while in further studies, e-nose systems have been integrated with consumer electronics, such as both refrigerators and meat coolers, to investigate their usefulness with smart packaging systems for different foods [20],[21].

Consumers want to have access to all kinds of food products that are fresh, have appropriate levels of microbial properties, have high nutritional value and are cost-effective. Rasekh and Karami [58] analyzed natural and industrial fruit juices with artificial neural networks using machine odor sensors. Using PCR method to measure the discrimination power of sensors, the authors focused on developing a cost-effective e-nose system to control the odor quality of foods. Pulluri and Kumar [55] proposed an efficient and integrated e-nose system to classify beef quality and estimate the microbial population in beef. The authors implemented the e-nose system on 18 datasets and presented the results using an approach including data collection, component analysis, classification and output analysis. Huang and Gu [59] proposed a neural network method and a random forest regressor for the quantitative detection of beef adulterated with pork using e-nose data. The random forest regressor proposed by the authors improves the regression performance and is compared with other well-known machine learning methods in the literature. Sanaeifar et al. [57] have been present e-nose applications in the food sector to ensure food health and safety, challenges faced in this field and future perspectives in a review study. In another review study by Tan and Xu [54], the applications of e-nose and e-tongue in determining the quality of foods were examined. In the related study, artificial intelligence based pattern recognition algorithms are introduced and compared. Roy and Yadav [56] comprehensively discussed the contributions of a gas sensor-based e-nose system for detecting food product counterfeiting. The reader can refer to these studies for more information on the e-nose. Tatli et al. [60] investigated the effects of varying urea-nitrogen fertilizer application rates on volatile organic compound emissions from cucumber fruits using an experimental metal oxide e-nose device. The authors analyzed the electrical signals from the e-nose sensor using 4 classification methods, including quadratic discriminant analysis and support vector machines. At the end of the study, volatile organic compound emissions combined with e-nose and quadratic discriminant analysis were shown to be promising for monitoring the relevant values of cucumber fruit. In another study, fraud samples in extra virgin olive oil were detected with e-nose and ultrasound systems [61]. In the related study, it was revealed that Gradient Boosting Classifier and Support Vector Machines methods gave the highest classification accuracy value.

While some gasses cause rot in fruits or are formed as a result of rot, others are used to protect against decay. For example, the application of carbon monoxide gas after the harvest of jujube fruit to control a type of spoilage called Alternaria rot has been studied by Zhang et al. [22]. The reliable measurement of gas emission density during the ripening of foods and estimating decay using the most appropriate method is critical issue in the food safety field. Image processing and hyperspectral imaging techniques provide high performance, but the techniques are very expensive. However, e-nose systems designed using Single Board Computers (SBCs) and Field Programmable Gate Arrays (FPGAs) achieve similar performances despite their low power and low cost [23]-[26].

Over the last quarter-century, the IoT concept has gained great popularity as a result of access to the modern wireless communication environment and is considered a technological revolution. IoT is essentially a combination of Radio-Frequency Identification (RFID) tags, sensors, actuators and devices with a mobile or fixed communication capability working together for a common purpose [27].

IoT offers unique solutions to many industrial sectors, such as automotive, telecommunications, underground research, energy, security, environmental research, agriculture, farming, food quality tracking, recycling, logistics and supply chain management [28]. Regarding the possible market shares of IoT applications developed or to be developed for different fields in 2025, the areas where IoT is expected to be used the most are healthcare and manufacturing, respectively [29]. Then electricity (energy) comes with a share of 7%. On the other hand, it is predicted that this rate will have a share of approximately 4% for IoT studies in the field of agriculture by 2025 for many other sectors, also there are various application examples today [29].

In interrelationships of IoT, things -oriented- vision includes sensors, actuators, etc. with unique addresses and IDs [27], [29]. It deals with the process of collecting information/data from a certain environment by devices [30]. Internet vision is about the communication process between small objects, in which devices of different sizes and with different properties use different wired or wireless methods to communicate with each other [31]. With the combination of things and internet vision, a large amount of data is collected in IoT applications. Semantic vision refers to the processes involved in the use and processing of large amounts of data collected by IoT devices of different sizes and features [32].

E-nose technologies are IoT-based systems that are inspired by the sense of smell, and consist of computer systems and sensors, that are in active use in a broad range of applications, from human health to food safety [33]. Gas sensors and machine learning techniques can be applied for the analysis of volatile organic gasses in a wide range of application areas, from the healthcare to the food sector [34]-[39].

Avocado is considered an important agricultural-based foodstuff due to its growing global market share. According to a 2021 agricultural products market report, 7.1 million tons of avocado was produced around the world in 2019, marking a 6.1% increase in production compared to the previous year [40].

Avocado (*Persea Americana* Mill.), belonging to the Lauraceae family, is endemic to Central America. It is a high-calorie fruit with a rich content of vitamins E, C, B6 and B9, potassium, dietary fiber and fat. It contains approximately 20% fat, 2% protein and 1.5% dietary fiber, and contains also bioactive phytochemicals with antioxidant properties, such as tocopherols, carotenoids and sterols [41]-[43]. Globally, there are more than 500 varieties of avocado, with different sizes, shapes and weights, although most are not produced commercially due to their insufficient protein and fat content and their unsuitability for transport. The most well-known and marketed avocado varieties in the global market are Hass and Fuerte [40],[44].

Freshly harvested, unripe avocados have a very firm texture. Unlike other fruit, they soften and ripen after harvesting, making their storage conditions very important [42]. The optimum temperature for ripening is 15-20 °C, as below this temperature ripening occurs slowly, while temperatures above 25 °C can lead to an undesirable structure and an unpleasant taste as a result of decay and irregular ripening. The ripening of avocado is completed in 5-7 days at room temperature, during which ethylene is released and the respiratory rate increases. For this reason, in the avocado food sector, the fruit are ripened in the presence of ethylene and kept under controlled storage temperatures before processing. It is of great importance to preserve the color during ripening, which is one of the most important parameters for the consumer [40],[43].

In this study, for the first time in literature, the decay of avocado was monitored in a controlled experimental environment using an Arduino-based temperature and gas monitoring system, while a Support Vector Machine (SVM), which is one of the novel machine learning methods, was used to detect decay from the obtained data. Since it has achieved successful results in the field of food in the literature, the use of SVM has been preferred [37],[48].

The remainder of this study is organized as follows. The introduction and related literature are presented in first section. The details of the material and method are given in Section 2. The details of the data retrieval and used SVM model are provided in Section 3. The results are presented and discussed in Section 4. Finally, in conclusion section, the paper is summarized, and some future research directions are given.

2 Material and method

2.1 Avocado and experimental environment

The three Fuerte avocado (*Persae Americana Mill.*) samples used in this study were obtained from a supermarket in Denizli, Turkey. The unripe avocado samples were placed in a 90 lt capacity office-type refrigerator with an F energy class.

2.2 E-Nose

An Arduino-based e-nose system designed for the study monitored the avocado fruit ripening, with decay data (input) collected from eight sensors using an Arduino Due microcontroller based on 32bit ARM core. Highly sensitive input data was collected with e-nose system. The design purpose of the system is to read and filter the signals come from the sensors to provide input to the SVM model, as well as to detect if there are any rotten avocados in the refrigerator. The e-nose, the circuit diagram of which is presented in Figure 1, is programmed to store the data collected from the sensors to the SD card for SVM model training. The circuit also contains a buzzer that provides an audible warning in the event of any problems that occur in the sensors or SD card.

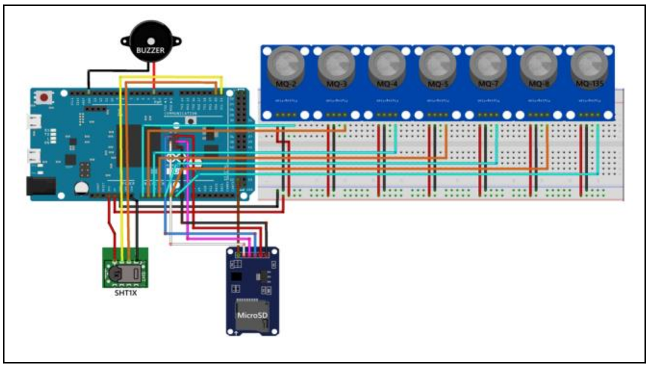


Figure 1. E-Nose circuit diagram.

The MQ-2, MQ-3, MQ-4, MQ-5, MQ-7, MQ-8 and MQ-135 gas sensors integrated with the designed e-nose are sensitive to many gasses in the environment with concentrations of between 300 and 10000 ppm. The sensors operate at temperatures between -20 °C and 50 °C and are powered by a 5V adapter. They produce analog output values, which affected at different levels by almost all gasses, including carbon monoxide (CO), methane (CH_4), alcohol (C_2H_5OH), hydrogen (H_2), propane (C_3H_8), benzene (C_6H_6), ethylene (C_2H_6), butane (C_4H_{10}), nitrogen (N_2), nitrogen oxides (NO), ammonia (NH_3) and carbon dioxide (CO_2), and while they are sensitive to more than one gas, they produce a single output. For example, the MQ-3 sensor is highly sensitive to alcohol, while the MQ-4 sensor is highly sensitive to methane and butane gasses. If the two sensors are used together, an increase in the alcohol concentration in the environment will result in a higher increase in the MQ-3 sensor value than in the MQ-4 sensor. On the other hand, the MQ-6 sensor is very similar to the MQ-5, and the two produce the same results in the working environment, and so for this reason, no MQ-6 sensor was included in the e-nose system. Similarly, the MQ-9 sensor is not included in the study due to the similarity of its results with those of the MQ-4 sensor. The gas sensors used for this purpose are sensitive to many gases simultaneously rather than concentrating on a single specific gas. For this reason, we aim to increase the number of features to best classify the densities of different gases in the environment using SVM. The MQ-6 and MQ-9 sensors are excluded from the system because they cannot produce independent results. The main goal in this study is to obtain gas density values by a machine learning method on the effectiveness of the gasses in a closed environment using much cheaper and faster sensors, instead of finding the exact density of each gas using very expensive sensors. For more detailed information about sensors, [50] and [51] studies can be examined.

2.3 Data retrieval

In this study, first of all, avocado samples with the designed e-nose were placed in the refrigerator to create the training data set, and the measurement results obtained from the sensors were recorded on the SD card. This process can be expressed as an algorithm comprising three sub-processes:

1. *Initialization*: In the first sub-process, the drivers and connection pins of the temperature sensor (HTU21D), gas sensors and SPI communication protocols are defined. Then, the float type variables that will record the output of each sensor are defined for memory allocation. This sub-process was completed with the creation of the file on the SD card,
2. *Checking*: It is checked whether the drivers loaded in the first subprocess generate an error code. For example, if a temperature sensor produces a code '998' value and any gas sensor produces a code '0' or '1023' values, it means system isn't working properly. After checking the sensors, the data file is prepared to allow the writing of the data on the SD card, and communication is checked. If an error occurs on the sensors or on the SD card, a digital output is connected to the reset pin of the Arduino and is sent a signal to the buzzer, depending on the error code. In such cases, the system is reset, and the first sub-process is started again. Otherwise, the third sub-process, involving data reading, is started,
3. *Data Reading*: The data read from the temperature and gas sensors are reset, and cumulative results are obtained by tracking the generated data for one second using an index. Thus, the filtered sensor values are obtained by calculating the averages of the data collected for one second. In this wise, sensor values are smoothed by the average filter. The gas filtered data values are normalized by dividing by 1023, and the temperature data is normalized by dividing by 15. If the temperature value is above 15 °C, all sensor values are deleted, and a third sub-process is started again, as the refrigerator can be seriously affected by the outside temperature during opening and closing. In other words, after the indoor temperature drops below 15 °C, the disturbing effects of the external environment are sufficiently reduced, and more reliable data can be recorded. In the last step of the third sub-process, the received and filtered data is written on the SD card with a timestamp. The flowchart of this sub-process is presented in Figure 2.

Data collection in the study was carried out over 35 days. For the first 13 days, 2/3 of the avocados in the refrigerator were kept under room conditions for 21 hours after measurement, accelerating their maturation process, and their decay was observed at the end of the 13th day. Images of avocados on day 0, and on the 13th, 19th and 47th days are given in Figure 3.

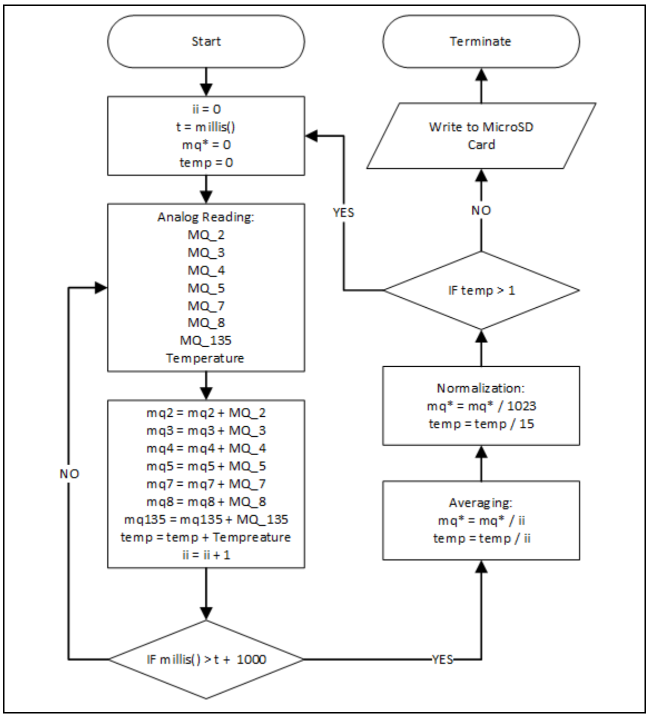


Figure 2. Data reading sub-process flowchart.

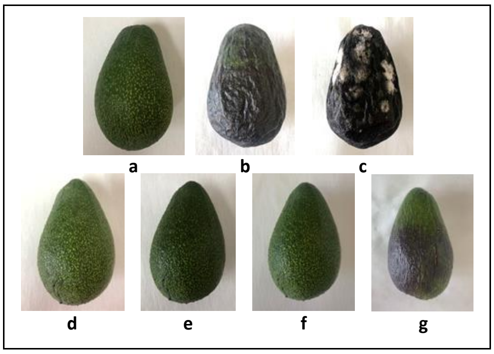
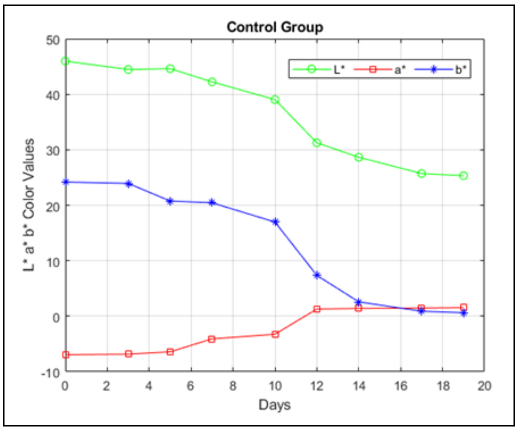
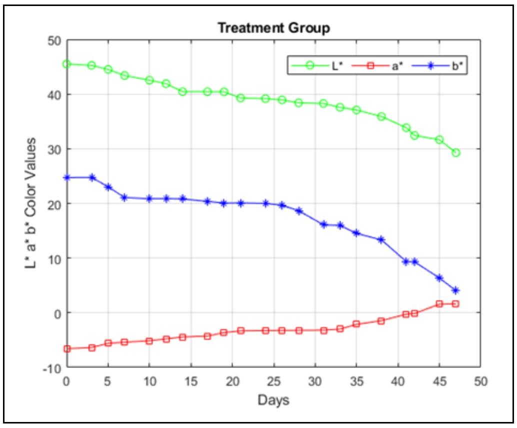


Figure 3. Images of avocados in the experimental study. (a): Day 0 of the control group. (b): 13th day of the control group. (c): 19th day of the control. (d): Day 0 of the experimental group. (e): 13th day of the experimental group. (f): 19th day of the experimental group. (g): 47th day of the experimental group.

As can be seen from the images, the control group spoiled on the 13th day while the experimental spoiled on the 47th day. The colors of the avocados were measured using a colorimeter (Miniscan XE, Hunter Assoc. Lab., Reston, Virginia, USA). The color values were expressed as L^* (whiteness/darkness), a^* (redness/greenness) and b^* (yellowness/blueness). The Hunter L^*, a^* and b^* values of the control group and experimental group are presented in Figure 4(a) and Figure 4(b), respectively. According to the color analysis, it was determined that the 13th day L^*, a^* and b^* values of the control group were similar to those of the 47th day L^*, a^* and b^* values of the experimental group. As a result of the color analysis, the decay of the avocados seen in the images was supported by L^*, a^* and b^* values. L^*, a^* and b^* data are used in this study to validate the results of SVM, which is a supervised model. However, they were not used as features in the training and testing process.



(a)



(b)

Figure 4(a): L^*, a^* and b^* measurement values of the control group. (b): L^*, a^* and b^* measurement values of the treatment group.

All data obtained from 8 sensors are shown in Figure 5. As can be seen from Figure 5, the sensors are affected by the temperature and gases formed. Blue and red dots indicate fresh and rotten samples, respectively. As mentioned in the Data Retrieval section, the temperature values are normalized by dividing by 15. Considering that the data in other sensors are close to each other, it is clear that one sensor will not be sufficient for classification. As mentioned earlier, avocados were labeled as spoiled in data taken after day 13.

2.4 Support vector machine

The Support Vector Machines, proposed by Vapnik [52], [53], is a highly successful machine learning method that aims to create a linear model of the best hyperspace for the effective separation of the samples to be classified. The main aim is to find the separating margin with the maximum total perpendicular distance to the closest samples (support vectors) [45]. In real-world problems, however, a linear margin that separates the examples to be classified cannot usually be defined, and so for this reason, nonlinear margins can be created by redefining the distance between the samples using kernel functions.

In e-nose applications, the use of polynomial [46] and radial basis function (RBF) [47],[48]-based kernel functions increases performance.

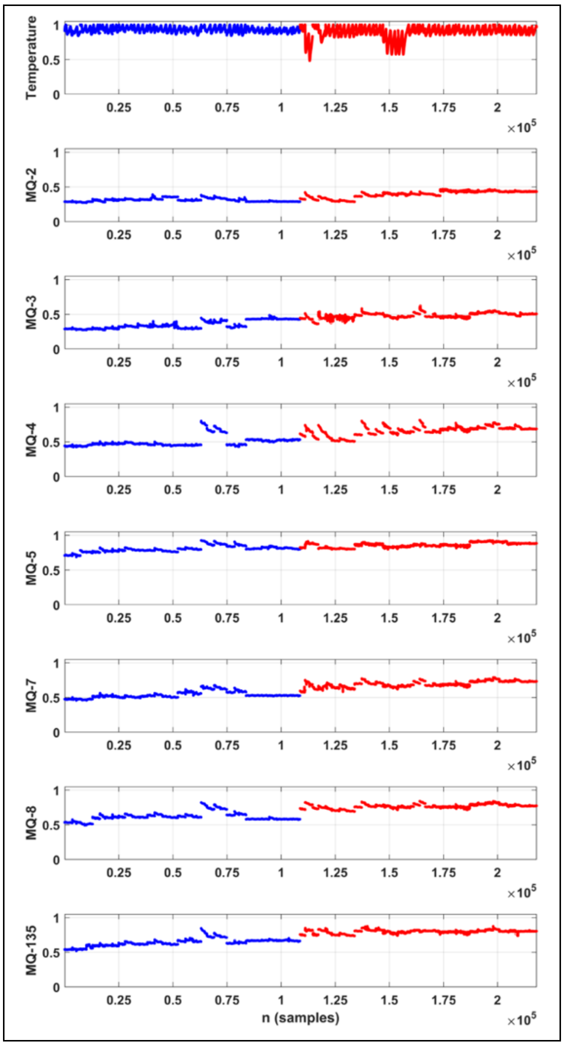


Figure 5. Normalized sensor data.

In this study, two different classes–fresh and decayed avocados–are defined $C = \{-1,1\}$, and each sample taken is expressed as $\{x_i, y_i\}$, $i = 1,2, \ldots, N$, $y_i \in \{-1,1\}$, $x_i \in R^L$ with the index i. Here, the x_i vector is the feature vector of i^{th}sample. The feature vector is comprised of the temperature, MQ-2, MQ-3, MQ-7, MQ-8, MQ-135, MQ-5 and MQ-4 values obtained during the normalization processes presented in Figure 2. The number of features used is 8 ($L = 8$).

The value of y_i containing the class information in the i^{th} sample takes a value of -1 if taken from a fresh avocado, and 1 if taken from a decayed avocado. In this case, the model that will determine which class any x sample belongs to can be defined using Equation (1).

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b \qquad (1)$$

in which α_i corresponds to the weighting coefficients of the model and b is the bias term.

These coefficients are obtained by solving the objective function specified in Equation (2) with N training data under the *Karush-Kuhn-Tucker* conditions using quadratic programming [49].

$$min\frac{1}{2}\sum_{i=1}^{N}\sum_{k=1}^{N}\alpha_i\alpha_k y_i y_k K(x_i,x_k)-\sum_{i=1}^{N}\alpha_i$$
$$\sum_{i=1}^{N}\alpha_i y_i=0 \qquad (2)$$
$$\alpha_i\geq 0;\ i=1,2,\dots,N$$

The kernel function $K(x_i, x_k)$, which allows a linear model to express a nonlinear margin, is basically a distance definition between two points. The SVM model becomes linear when the $K(x_i, x_k) = x_i^T . x_k$ function is used for the Euler distance. While the q^{th} order polynomial kernel functions are used as the basis for nonlinear classification problems are expressed with the $K(x_i, x_k) = (x_i^T . x_k + 1)^q$ Equation, the most frequently used Gauss Kernel in the literature is defined with $K(x_i, x_k) = e^{-\frac{\|x_i-x_k\|^2}{2s^2}}$ [49]. Here, s is a scalar quantity specified by the user. In this study, many different kernel functions are used, although it was observed that the best results are obtained with RBF.

3 Results and discussion

Since the e-nose designed in this study is Arduino-based, its power consumption is economic and dimensions are very small, and it can collect data over a long period, although its processing power is low, and its memory is very small. As can be seen from Equation (1), SVM needs attributes of all support vectors and coefficients as many as the number of support vectors to test and classify a new sample. For this reason, it has become essential to complete the model using the least number of parameters from the large amount of data collected during the study.

Firstly, models with different training data numbers were created randomly, and the support vectors of these models were examined. In this stage, all training data were randomly and equally selected from two different classes. Different training processes were made 100 times, which has 100,000 validation data. In each training, the remaining data were used as test data. The selection of validation and test data was also arranged randomly, and the test and validation errors obtained from 100 different trainings are presented in Figure 6(a).

As can be seen in Figure 6, the test and validation errors are very close to each other, reveling the number of Monte Carlo simulations to be sufficient. Based on the Monte Carlo simulation results, the number of Train data was set to 112, the first value at which the Test and Validation performance exceeded 99%. Figure 6(b) shows that the Train performance for the same number of train data is 99.8036%. Similarly, Figure 6(c) shows that the number of support vectors produced by the SVM for the selection of 112 train data is 30.

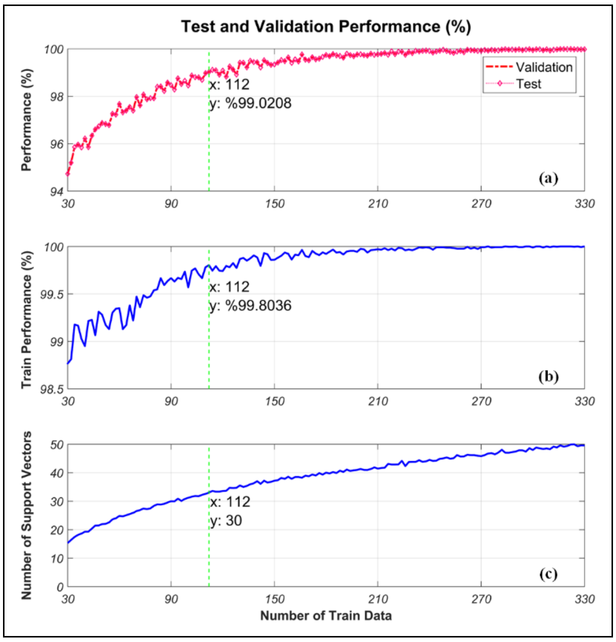


Figure 6(a): Test and validation performance. (b): Train performance. (c): Number of support vectors.

In line with these results, the number of training data for the model was selected as 112, and another 200 trainings were carried out for the best model using the randomly selected training data. The best SVM model obtained 29 support vectors during these implementations. The α_i coefficients, x_i support vectors and b the bias term of the model are given in Appendix (Table A.1: Train Data and Table A.2: SVM Parameters), and the performance of the model after 100,000 validations and the 132,780 test data are shown in Table 1.

As can be seen from Table 1, the selected model produces no false positives for any fresh sample. To measure the mathematical performance of the model, the accuracy Equation 3(a), sensitivity Equation 3(b) and specificity Equation 3(c) criteria, which are commonly used in binary classifiers, were preferred [47].

$$Accuracy=\frac{tp+tn}{tp+fp+tn+fn} \qquad 3(a)$$

$$Sensitivity=\frac{tp}{tp+fn} \qquad 3(b)$$

$$Specificity=\frac{tn}{tn+fp} \qquad 3(c)$$

Table 1. Actual and predicted values according to test and validation.

Validation

		Prediction	
		Rotten	Fresh
Actual	Rotten	True Pos (50243)	False Neg (99)
	Fresh	False Pos (0)	True Neg (49658)

Test

		Prediction	
		Rotten	Fresh
Actual	Rotten	True Pos (66707)	False Neg (138)
	Fresh	False Pos (0)	True Neg (65935)

In Equation 3, True Positive (*tp*), True Negative (*tn*), False Positive (*fp*), and False Negative (*fn*) values must be counted from the output of the model. These values correspond to the output of the model being 1 when all avocados in the refrigerator are fresh, the output of the model being -1 when there are any decayed avocados in the refrigerator, the output of the model being 1 when there are decayed avocados in the refrigerator, and the output of the model being -1 when there is no decayed avocado in the refrigerator.

As can be seen from Table 2, the selected model achieves an accuracy performance of 99.9% with only 29 support vectors and 100% specificity, since it produces no false positive values.

Table 2. Validation and test performance of selected model.

	Validation	Test
Accuracy	%99.901	%99.896
Sensitivity	%99.803	%99.794
Specificity	%100	%100

4 Conclusion

The production, transportation and storage of food products, especially agricultural products, are of critical importance in meeting the nutritional needs of the growing world population in terms of food safety, energy and carbon footprint. It is clear that any improvements made in one or more of these areas will both directly and indirectly serve the Sustainable Development Goals determined by the United Nations. Using rapidly developing technologies and designs based on technological innovations to this end becomes inevitable, in addition to the increasing complexity and importance of the food supply chain over time. Thus, applications of technological solutions that support food safety in all areas of the supply chain are becoming widespread.

In this study, for the first time in literature, the maturation of avocado was monitored using an Arduino-based system, called e-nose. This constitutes the original aspect of the study. SVM method was used to detect decay data from sensors. With eight features used for machine learning, a test and validation success of over 99% was achieved. Another important contribution is the developed system and algorithm can be used for the classification of decay in food products in a very low-cost way and with an acceptable margin of error.

As future directions of this study, due to the adaptive structure of the developed system, higher performance values can be obtained through the use of more advanced sensors or a more complex single-board computer. Furthermore, this system, while being innovated within this specific field, can be easily adapted to other food products, depending on their biological, physical and chemical properties, alone or in combination. Also, more robust machine learning systems can be created through the application of commonly used classification methods, such as Random Forest and Bayesian, either alone or in combination, aside from SVM. The developed system and algorithm can be used in refrigerators and other cold storage areas to increase the living standards of end-users and to prevent product losses. Moreover, in situations when the distance between production area and market is large, similar systems can be integrated with logistics vehicles at affordable prices. In this way, the manual control systems required to detect decay during storage and transportation can be replaced by automated systems, reducing costs and enabling the end consumer to access these food products at lower prices. Additionally, in individual cases, food waste can prevent thanks to the early warning system for decay detection.

5 Author contribution statements

In the scope of this study, Mehmet Doğan ELBİ contributed to formation of the idea, assessment of obtained results, the methodology, writing-original draft and software development; Ezgi ÖZGÖREN ÇAPRAZ contributed to conceptualization, experimental study, the spelling and checking the article in terms of content; Emre ŞAHİN contributed to formation of the idea, conceptualization and methodology; Mehmet Ulaş KOYUNCUOĞLU contributed to formation of the idea, the methodology, investigation, supervision, writing-review & editing, literature review and examining the results; Can TUNCER contributed to design and experimental study.

6 Ethics committee approval and conflict of interest statement

"There is no need to obtain permission from the ethics committee for the article prepared".

"There is no conflict of interest with any person/institution in the article prepared".

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Appendix

Table A.1. Train data.

Temp.	MQ_135	MQ_2	MQ_3	MQ_4	MQ_5	MQ_7	MQ_8	Class	SV
0.6171	0.5477	0.2847	0.2906	0.4400	0.7266	0.4795	0.5507	0	1
0.6694	0.5454	0.2744	0.2754	0.4351	0.7580	0.4648	0.5096	0	0
0.7092	0.5460	0.2744	0.2763	0.4355	0.7588	0.4656	0.5118	0	1
0.7729	0.5840	0.2881	0.2890	0.4588	0.7603	0.4787	0.5176	0	0
0.7164	0.6099	0.2959	0.2886	0.4785	0.8104	0.5355	0.6447	0	0
0.6895	0.5907	0.2823	0.2746	0.4594	0.7803	0.5097	0.6140	0	0
0.6688	0.5942	0.3028	0.2917	0.4697	0.7764	0.5126	0.6124	0	0
0.7582	0.5954	0.3097	0.2940	0.4727	0.7765	0.5167	0.6133	0	0
0.7625	0.6225	0.3161	0.3213	0.4738	0.7939	0.5019	0.6233	0	0
0.6688	0.6142	0.3126	0.3174	0.4729	0.7808	0.4958	0.6087	0	0
0.7930	0.6523	0.3276	0.3376	0.4968	0.8184	0.5247	0.6553	0	0
0.7630	0.6417	0.3271	0.3325	0.4919	0.8057	0.5156	0.6408	0	0
0.7674	0.6417	0.3271	0.3323	0.4922	0.8057	0.5156	0.6413	0	0
0.8122	0.6406	0.3262	0.3299	0.4907	0.8053	0.5162	0.6403	0	0
0.7620	0.6224	0.3126	0.3204	0.4729	0.7932	0.5080	0.6182	0	0
0.7413	0.6144	0.3084	0.3446	0.4674	0.7871	0.5021	0.6095	0	0
0.6787	0.6180	0.3204	0.3389	0.4756	0.7869	0.4980	0.6113	0	0
0.6177	0.6115	0.3164	0.3329	0.4712	0.7802	0.5151	0.6036	0	0
0.6481	0.6143	0.3165	0.3330	0.4754	0.7801	0.5148	0.6044	0	0
0.7620	0.6348	0.3115	0.3223	0.4570	0.7871	0.5291	0.6387	0	0
0.6585	0.6477	0.3214	0.3231	0.4688	0.7920	0.5363	0.6490	0	0
0.6585	0.6220	0.3589	0.3321	0.4480	0.7731	0.5127	0.6194	0	0
0.7741	0.6267	0.3613	0.3321	0.4540	0.7753	0.5195	0.6223	0	1
0.7206	0.6235	0.3567	0.3301	0.4551	0.7703	0.5146	0.6152	0	0
0.7516	0.6163	0.3545	0.3711	0.4492	0.7646	0.5068	0.6079	0	0

Table A.1. Continued.

Temp.	MQ_135	MQ_2	MQ_3	MQ_4	MQ_5	MQ_7	MQ_8	Class	SV
0.7620	0.6172	0.3545	0.3693	0.4500	0.7647	0.5075	0.6084	0	1
0.6999	0.6708	0.3095	0.2983	0.4512	0.8083	0.5719	0.6279	0	0
0.6340	0.6563	0.3047	0.2929	0.4502	0.8007	0.5655	0.6182	0	0
0.6585	0.6572	0.3027	0.2930	0.4531	0.7998	0.5654	0.6182	0	0
0.7340	0.6797	0.3135	0.3037	0.4555	0.8222	0.5857	0.6494	0	0
0.6688	0.6714	0.3093	0.2959	0.4482	0.8162	0.5757	0.6377	0	0
0.7496	0.6904	0.3060	0.2969	0.4510	0.8105	0.5790	0.6348	0	1
0.7206	0.6543	0.3086	0.2977	0.4511	0.8008	0.5557	0.6145	0	0
0.7516	0.6563	0.3105	0.2986	0.4580	0.7966	0.5596	0.6123	0	0
0.6901	0.6535	0.3086	0.2969	0.4561	0.7956	0.5576	0.6106	0	0
0.7413	0.8154	0.3696	0.4268	0.7682	0.9200	0.6509	0.8097	0	1
0.8339	0.7997	0.3604	0.4122	0.7630	0.9162	0.6398	0.8020	0	1
0.7200	0.7273	0.3380	0.3865	0.6661	0.8741	0.6330	0.7411	0	1
0.7516	0.7396	0.3450	0.3809	0.6880	0.8820	0.6447	0.7525	0	0
0.8137	0.7421	0.3471	0.3833	0.6888	0.8825	0.6472	0.7542	0	1
0.7930	0.7238	0.3343	0.4095	0.6420	0.8719	0.6279	0.7339	0	1
0.6481	0.6246	0.3105	0.3033	0.4576	0.8331	0.5675	0.6341	0	0
0.7396	0.6279	0.3115	0.3076	0.4619	0.8359	0.5730	0.6372	0	0
0.6601	0.6358	0.2981	0.3293	0.4414	0.8724	0.6065	0.6630	0	1
0.6378	0.6372	0.3171	0.3276	0.4571	0.8564	0.5858	0.6548	0	0
0.6068	0.6347	0.3154	0.3244	0.4619	0.8506	0.5808	0.6494	0	0
0.6901	0.6641	0.2868	0.4287	0.5235	0.8019	0.5254	0.5830	0	0
0.7092	0.6639	0.2879	0.4316	0.5252	0.8027	0.5271	0.5850	0	0
0.6275	0.6624	0.2886	0.4303	0.5291	0.8057	0.5253	0.5820	0	0
0.7309	0.6768	0.2949	0.4436	0.5174	0.8325	0.5322	0.5892	0	0
0.7413	0.6765	0.2948	0.4427	0.5154	0.8329	0.5323	0.5895	0	1
0.7179	0.6778	0.2982	0.4385	0.5084	0.8427	0.5253	0.5986	0	0
0.6171	0.6667	0.2910	0.4599	0.5010	0.8301	0.5215	0.5831	0	1
0.6378	0.6695	0.2922	0.4443	0.5073	0.8301	0.5249	0.5847	0	0
0.6275	0.6640	0.2876	0.4294	0.5178	0.8145	0.5252	0.5806	0	0
0.6269	0.6602	0.2881	0.4305	0.5234	0.8042	0.5244	0.5820	0	0
0.0029	0.8198	0.3544	0.4304	0.6524	0.8761	0.6947	0.7910	1	1
0.9379	0.7822	0.3321	0.3955	0.5998	0.8855	0.6641	0.7552	1	1
0.9205	0.7743	0.3318	0.3945	0.5988	0.8848	0.6629	0.7547	1	1
0.7206	0.7526	0.3080	0.3623	0.5417	0.8678	0.6150	0.7319	1	1
0.6068	0.8340	0.3295	0.4864	0.6032	0.8360	0.6695	0.7564	1	0
0.8339	0.7847	0.3201	0.4464	0.5686	0.8193	0.6982	0.7364	1	0
0.5757	0.7790	0.3132	0.4847	0.5574	0.8163	0.6877	0.7306	1	0
0.5550	0.7741	0.3097	0.4913	0.5522	0.8127	0.6800	0.7252	1	0
0.5861	0.7729	0.3109	0.4178	0.5500	0.8121	0.6778	0.7235	1	1
0.8034	0.7566	0.2988	0.4652	0.5229	0.8066	0.6533	0.7123	1	1
0.5757	0.7724	0.3066	0.4782	0.5400	0.8134	0.6746	0.7248	1	0
0.5855	0.8076	0.3651	0.4865	0.5999	0.8687	0.6982	0.7564	1	1
0.7402	0.8061	0.3653	0.4860	0.6014	0.8626	0.6995	0.7544	1	0
0.7206	0.8489	0.4242	0.5462	0.7950	0.8874	0.7676	0.8232	1	0
0.6895	0.8520	0.4159	0.5283	0.7686	0.8974	0.7598	0.8191	1	1
0.7930	0.8405	0.3854	0.5187	0.6739	0.8726	0.7235	0.7870	1	0
0.7309	0.8242	0.3779	0.5106	0.6454	0.8798	0.7128	0.7771	1	0
0.4205	0.8012	0.4193	0.4985	0.7685	0.8390	0.6856	0.7863	1	1
0.3113	0.8044	0.4145	0.4809	0.7104	0.8335	0.6833	0.7751	1	0
0.3170	0.8042	0.4140	0.4803	0.7098	0.8336	0.6827	0.7749	1	0
0.6378	0.7956	0.4081	0.4703	0.6911	0.8263	0.6697	0.7679	1	0
0.2342	0.7704	0.3819	0.4464	0.6228	0.8249	0.6439	0.7391	1	1
0.6538	0.8040	0.4102	0.4745	0.6758	0.8498	0.6787	0.7751	1	0
0.6326	0.8083	0.4201	0.4736	0.6484	0.8539	0.6805	0.7644	1	0
0.7079	0.8086	0.4000	0.4730	0.6436	0.8525	0.6800	0.7637	1	0
0.6171	0.8135	0.3867	0.5037	0.6670	0.8611	0.7022	0.7803	1	0
0.6999	0.8001	0.4096	0.5526	0.7740	0.8785	0.7507	0.8253	1	0
0.7195	0.8095	0.4053	0.5464	0.7256	0.8736	0.7449	0.8163	1	0
0.6792	0.8134	0.4012	0.5371	0.7117	0.8730	0.7364	0.8090	1	0
0.7413	0.8085	0.3979	0.4661	0.6392	0.8508	0.6735	0.7595	1	0
0.7309	0.8077	0.3973	0.4667	0.6387	0.8506	0.6739	0.7592	1	0
0.6563	0.8013	0.3728	0.4632	0.6372	0.8368	0.6713	0.7513	1	1
0.7206	0.8086	0.3770	0.4707	0.6426	0.8432	0.6777	0.7588	1	1
0.6585	0.7998	0.3730	0.4603	0.6329	0.8340	0.6685	0.7491	1	0
0.7516	0.7943	0.4611	0.4690	0.6829	0.8668	0.6875	0.7602	1	0
0.5861	0.7910	0.4541	0.4627	0.6768	0.8652	0.6833	0.7559	1	0
0.5757	0.7966	0.4626	0.4695	0.6831	0.8707	0.6889	0.7614	1	0

Table A.1. Continued.

Temp.	MQ_135	MQ_2	MQ_3	MQ_4	MQ_5	MQ_7	MQ_8	Class	SV
0.6171	0.7959	0.4624	0.4692	0.6839	0.8704	0.6887	0.7610	1	0
0.7413	0.7938	0.4366	0.4639	0.6986	0.8505	0.6875	0.7550	1	1
0.7271	0.7936	0.4371	0.4641	0.6987	0.8507	0.6878	0.7552	1	0
0.6291	0.7907	0.4221	0.5012	0.6837	0.9014	0.7203	0.7858	1	1
0.7827	0.7959	0.4293	0.5081	0.6869	0.9057	0.7271	0.7891	1	1
0.6688	0.8085	0.4334	0.5203	0.6992	0.9054	0.7331	0.7999	1	0
0.7827	0.8096	0.4346	0.5230	0.6997	0.9080	0.7383	0.7989	1	0
0.5861	0.8083	0.4390	0.5242	0.6990	0.9117	0.7350	0.7992	1	0
0.5861	0.8215	0.4403	0.5303	0.7414	0.9105	0.7529	0.8112	1	0
0.6275	0.8204	0.4400	0.5303	0.7383	0.9111	0.7511	0.8054	1	0
0.7783	0.8275	0.4507	0.5388	0.7392	0.9186	0.7581	0.8164	1	1
0.6068	0.8316	0.4453	0.5372	0.7545	0.9128	0.7662	0.8187	1	0
0.6656	0.8019	0.4277	0.5156	0.6898	0.9040	0.7295	0.7931	1	0
0.7102	0.8063	0.4344	0.5196	0.6931	0.9124	0.7370	0.7987	1	0
0.6585	0.7960	0.4221	0.4995	0.6922	0.8702	0.7264	0.7654	1	0
0.7620	0.8058	0.4351	0.5055	0.6998	0.8821	0.7367	0.7761	1	0
0.7528	0.8038	0.4316	0.5000	0.6815	0.8832	0.7266	0.7709	1	0
0.7723	0.8042	0.4309	0.5014	0.6831	0.8839	0.7286	0.7726	1	0
0.7413	0.8056	0.4334	0.5046	0.6848	0.8803	0.7319	0.7738	1	0

Table A.2. SVM parameters.

Alpha	**Bias**	**Mu**	**Sigma**
0.64042	0.1872	0.68133	0.12059
0.36753		0.72517	0.08696
0.09891		0.35603	0.05606
0.29267		0.41605	0.08537
0.62859		0.58172	0.11033
1		0.8379	0.04513
0.58738		0.62232	0.09053
1		0.69949	0.08627
1			
1			
0.83243			
0.28562			
0.64054			
0.68304			
1			
1			
1			
0.79191			
0.70656			
0.02644			
0.43264			
0.39498			
0.44039			
0.00695			
0.40416			
0.57158			
0.23997			
0.65077			
0.02469			