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Pistachio Classification Based on Acoustic Systems and Machine Learning

Yavuz Turkay[*], Zekiye Seyma Tamay
Department of Electric Electronic Engineering, Sivas Cumhuriyet University, Sivas, Turkiye
[*]yturkay@cumhuriyet.edu.tr; 20209233012@cumhuriyet.edu.tr

***Abstract*—An acoustic emission and machine learning-based system for pistachio classification has been developed, utilising Mel frequency cepstral coefficients (MFCC) for feature extraction and a support vector machine (SVM) for classification. The study found that closed-shell pistachios produce different frequency components than open-shell pistachios when they hit a steel plate. Audio signals were recorded using a high-sensitivity carbon microphone and a MATLAB Analogue Input Recorder. These recordings were processed with a Hamming window to reduce ambient noise.**

MFCCs, a leading method for extracting audio signal features, were used to differentiate between open- and closed-shell pistachios. The extracted features were input into the fit classifier support vector machine (FITCSVM) algorithm for classification, which performs binary classification on low- or medium-sized data sets. The study achieved high accuracy in distinguishing between open- and closed-shell pistachios, highlighting the potential of this system for the pistachio industry to improve product quality and processing efficiency.

In conclusion, the MFCC and support vector machine (SVM) algorithms effectively classified the pistachios by analysing acoustic emissions. This innovative approach shows promise in the development of more efficient methods in the processing of agricultural products.

***Index Terms*—Pistachio; Classification; Impact acoustic; MFCC; SVM.**

I. INTRODUCTION

Pistachio is a hard shell fruit that belongs to the genus Pistacia. It is produced in large quantities in Mediterranean countries and in terms of cultivation area around the world; it is one of the most popular hard shell fruits, ranking sixth after almonds, walnuts, cashews, hazelnuts, and chestnuts [1]–[4]. Pistachio (Pistachio Vera) is a xeric fruit species that grows in the world, especially between 30 ° and 45 ° parallels, in regions where summers are hot and dry and winters are cold and rainy [5]. Their roots are quite long and deep because when pistachio trees are planted in weak soils and not fertilised, they grow by extending their roots much further than they were in their initial state to access the food and water they need [6]. The upper part of its leaves is bright and the lower part is dull, and its fruits are in clustered. These clusters are called “Cumba” and the pistachio fruits are 10 mm–20 mm in length and 6 mm–12 mm in width. It has different shapes in width, from a long oval to a sphere. The inside is soft and usually red, while the outer shell is hard and some of it opens while the fruit is on the tree during ripening [7].

Pistachios are one of the most nutritious nuts [8]. Pistachios have 562 calories in a 100 g serving and are a rich source of protein, various dietary minerals, calcium, dietary fibre, vitamins B5 and B6, vitamin E, and thiamine [9], [10]. Pistachios are known to be beneficial in many areas, especially in heart health [11], [12].

It is estimated that pistachios have been grown in Iran for 3000–4000 years. According to the Food and Agriculture Organization (FAO), Iran, which accounts for 60 % of the global pistachio market, has become the world’s largest pistachio producer, and in the Iranian economy, pistachios have a significant share among non-oil export products [13], [15]. Iran is followed by the United States of America in second place in pistachio production [16], [17]. Although pistachio production has an important place in Turkey, it ranks third in the world after Iran and the United States. [18], [19].

The production, marketing, storage, and processing of pistachios, an agricultural product, is a very important process [3]. Three steps may be important in the peanut processing process: the detection of uncracked peanuts, the separation of hollow peanuts from the filled ones, and the classification of peanuts according to their size, shape, healthiness, morphological, and aesthetic features. Currently, the buoyancy principle of water is used to separate empty pistachios [27]. However, the moisture content of the pistachios placed in water increases, which causes the growth of mould that causes alfa toxin. A complete system has not yet been developed to classify pistachios containing foreign matter and kernels, shells or particles, having various types of defects, mould, insect damage, and rotten pistachios [28].

Crack detection and classification in Siirt pistachios is currently done manually by workers using primitive methods. Considering food hygiene, this method has health drawbacks. In recent years, mechanical, acoustic, and optical methods have been frequently used in the classification of agricultural products [29], [31].

Some machine learning algorithms used for pistachios with determined physical properties include multilayer perceptron (MLP), support vector machine (SVM), and their ensembles (ESMs), k-nearest neighbour (kNN), regression tree, random forest (RF), Gaussian processes (GP), as shown in [32].

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Machine learning is the name given to algorithms that automatically identify important patterns among large data groups and model the identified problem based on data obtained from the problem environment [33]. In addition, machine learning is part of the subset of the artificial intelligence class that makes predictions about the data obtained [34]. It optimises the process based on data sets learnt from previous experiences [35]. Then it detects complex patterns and creates the most appropriate model taking advantage of computer computing power to make appropriate decisions [36]. Machine learning approaches fall into the general category of supervised and detect a model suitable for labelled data through the experimental measurement result [37].

Pearson and Toyofuku [29] introduced pulse acoustic emissions, which was the basis for a device that separated closed shell from open pistachios. The acoustic-based system does not cause such damage. The increased sequencing accuracy of the acoustic splitter, combined with the low cost of the hardware, provides a payback period of less than a year. Since algorithms are easily trainable, this has the potential to expand the number of applications that the acoustic sequencer currently has. This introduced system was later developed for use in wheat inspections to separate cracked hazelnut shells from undamaged hazelnuts, to separate underdeveloped hazelnuts from whole hazelnuts (and to detect insect-damaged kernel (IDK)) [38].

Vidyarthi, Tiwari, Singh, and Xiao [39] proposed a method that simultaneously accurately measures the size and mass of raw pistachios using machine learning and image processing. An image processing application was implemented by applying the recursive method to detect the kernel of an imaged pistachio and estimate its size based on the resulting pixels. The digital impression was used to estimate the number of pixels representing pistachios, their mass and size. The RF model was used for mass estimation using pistachio images. The measured average shell length of 100 pistachios was determined to be close to the estimated length. The mass of the pistachio kernels was estimated with 95 % accuracy [39].

Haff, Pearson, and Toyofuku [40] measure the feasibility of using colour imaging to distinguish both regular and small-shell pistachios in the pistachio process flow. Two algorithms have been developed to classify images of small shell pistachios. The first algorithm used discriminant analysis (DA) to evaluate features extracted from images based on histograms of red, green, and blue (RGB) pixel intensities. It found that the result of separating the kernels of regular-sized in-shell pistachios was 99.9 %, while the result of distinguishing small in-shell pistachios from their kernels was also 99.9 %. It has been observed to give an accuracy value of 85 %. The second algorithm used the kNN method, which evaluates features based on colour histograms and intensity gradient information. It has been concluded that the kNN method distinguishes shells from nuclei with the DA algorithm and matches its accuracy at 99.9 %.

In [41], a method is proposed to separate open shell pistachios from closed shell pistachios in a nondestructive manner. This proposed method uses a deep learning-based object detection algorithm. A Cartesian manipulator system equipped with a gripper and conveyor has been developed to physically separate pistachios. The main purpose of the dual-camera configuration, in addition, was preferred to detect one-sided separation on pistachios, which is difficult to achieve with the single-camera configuration. First, the object detection algorithm detects pistachios and determines their location with the bounding box. Then, the pistachios in both images taken with the cameras are matched by calculating their real coordinates, and the pistachios are separated by the Cartesian manipulator. The accuracy of the proposed method was found to be 98 % for open-shell pistachios and 85 % for closed-shell pistachios.

The development of innovative and cost-effective methods for the classification of agricultural products is of great importance in the agricultural sector. In this study, a new approach is proposed for the identification of open shell pistachios using acoustic emission sounds. This method avoids the need for excess materials and expensive sensors.

To eliminate noise, a Hamming window was applied between the percussion-recorded sounds. The pistachios were percussed against a plexiglass material, and the resulting signals were recorded using a piezo-microphone glued onto the plexiglass material. These signals were processed for feature extraction using Mel frequency cepstral coefficients (MFCCs). The extracted features are classified using SVM.

To verify the accuracy of the proposed system, open- and closed shell pistachios were used. After MFCC was applied to the open and closed shell pistachios of the samples, some of the data obtained were randomly assigned as training set and the rest of the data were randomly assigned as test set. The accuracy results obtained were 97.95 % for closed-shell pistachio samples and 97.2 % for open-shell pistachio samples.

In addition to these results, it was found that the percussion method is easy to use and has a wide range of applications compared to those of other methods for the evaluation of open and closed shells of pistachios.

II. MATERIALS AND METHODS

A. *Mel Frequency Cepstral Coefficients (MFCCs)*

Mel frequency cepstral coefficients (MFCCs) were developed by Davis and Mermelstein [42] and are a leading approach for extracting features of sound. MFCC is a preferred method, especially for speech signal analysis because the speech signal is made up of tones with different frequencies [43]. This method helps us to better understand the spectral properties of sound.

Speech signals contain tones of various frequencies. Between these frequencies, the perception capacity of the human ear varies. In this context, an approach known as the Koenig scale is used to understand the relationship between sound and frequency. In this approach, frequencies below 1000 Hz are evaluated linearly, and frequencies above 1000 Hz are evaluated logarithmically [45]. This implies that low frequencies are perceived differently from high frequencies.

According to [44], the pitch of a tone at 1 kHz, which is 40 dB above the perceptual hearing threshold, is defined as 1000 mel. This reference point is used to describe the relationship between the Mel frequency and the frequencies in Hz that the human ear can hear. Equation (1) provides a mathematical expression of this relationship. The Mel frequency scale is designed to better model the way the human ear perceives frequencies, resulting in more efficient processing of audio signals

$$f_{mel} = 2595\log\left(1+\frac{f}{700}\right). \tag{1}$$

In addition to these, Mel frequency cepstral coefficients (MFCCs) are one of the most preferred methods used in many speech and speaker recognition applications [46]. The usage areas of MFCCs are quite wide.

Figure 1 shows the workflow of the MFCCs. In MFCC, the feature extraction steps are passed through a filter that increases the frequency of the audio signal. The audio signal is then divided into a time period of 30 milliseconds by windowing. Then the Hamming window is used, multiplying with each framed signal. A fast Fourier transform (FFT) is then applied to each frame to obtain the large frequency. The largest frequency is then multiplied by triangular band filters to help reduce the size of the selected feature [47].

1. *Pre-emphasis, framing and windowing*

In this process, high-pass filters select frequencies above the cut-off frequency (fc) and attenuate lower frequencies [48]. Thus, low-frequency signals are removed using a high-pass filter [49]. This stage is used to emphasise the signal by filtering out high frequencies and to balance the speech signal spectrum [50]. The mathematical expression of the high-pass filter is given in (2)

$$H(z) = 1 - \mu z^{-1}, \tag{2}$$

where *H(z)* is the system function of the filter, *z* is the frequency of the signal, and l is typically between 0.9 and 1.0.

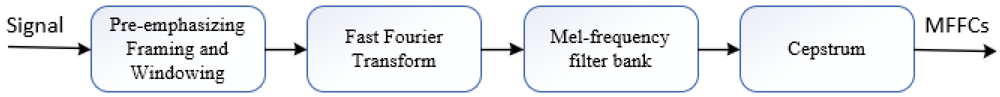


Fig. 1. Workflow of MFCCs.

Continuous audio signals are divided into adjacent frames with M and N sampled signals. The first frame consists of N sampled signals, and the second frame starts with M sampled signals after the first N sampled signals. In this way, the framed signals continue overlapping. This process continues until all speech signal samples are computed [51].

Windowing is the process of multiplying the waveform of an audio signal segment by a time domain with a specific shape. The Hamming window is used in the feature extraction stages, taking into account the next block and integrating all the nearest frequency blocks. It eliminates the fluctuations that appear after the Fourier transform [52]. Here, N represents the length of the frame. At this stage, the signal is segmented and each frame with N samples is multiplied by the window function w(n). Equation (3) refers to the Hamming window

$$w = 0.54 + 0.46\,\mathrm{Cos}\left(\frac{2\pi n}{N-1}\right). \tag{3}$$

2. *Fast Fourier transform*

FFT is an important transform method used in audio and acoustic applications. This method provides frequency information about a signal by transforming a signal in the time space into spectral components in the frequency space [53].

FFT is an algorithm that is used to quickly compute the Fourier transform of a discrete sequence. The inverse Fourier transform of the computed signal can be performed using inverse fast Fourier transform (IFFT).

FFT is widely used in many digital signal processing applications, such as speech recognition, signal processing, and acoustics [54].

3. *Mel filter banks*

Based on the theory of speech production and perception, filter banks commonly used in speech recognition applications are configured using the Mel scale [55]. Figure 2 shows triangular filter banks placed on a linear frequency scale using a nonuniform filter bank (NFB) of 24. These filter banks have a dense distribution at low frequency and a sparse distribution at high frequency. This suggests that filtering with the Mel scale emphasises low-frequency components, which are more important in speech analysis [56].

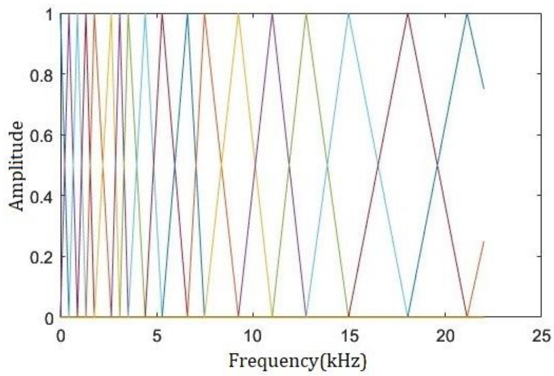


Fig. 2. Example of a 24-sample triangular bandpass filter.

4. *Cepstrum*

The cepstral representation of audio or acoustic signals best represents the local spectral properties of the signal in certain frequency ranges [44]. This cepstral representation is usually obtained by a process called “cepstrum”. As shown in Fig. 3, the cepstrum calculation process consists of three basic steps: discrete Fourier transform (DFT), logarithmic operation, and inverse discrete Fourier transform (IDFT).

In the first step, the signal is subjected to a discrete Fourier transform, which yields the spectral components of the signal. In the second step, the logarithm of these spectral components is taken. Finally, the cepstrum is obtained by applying the inverse discrete Fourier transform. This process provides a cepstral representation by relating the time-domain features of the signal to its frequency-domain features.

At the end of the process of obtaining the cepstral representation, the logarithm of the filtered spectrum is processed using Mel frequency filter banks. After this process, the MFCCs are obtained by applying the discrete cosine transform (DCT) [48]. MFCCs are used to better analyse the spectral characteristics of speech signals, as these coefficients are designed to better reflect how the human ear perceives frequencies [44], [48].

Fig. 3. Cepstrum flow diagram.

B. *SVM*

Support vector machines (SVM) is a machine learning model for classification and regression analysis developed by Vapnik *et al.* [58]. Basically, it is used to separate data points according to their classes or to create a decision boundary that best separates data points. The goal of SVM is to project the input vectors into a high-dimensional feature space and find the linear decision line that most accurately represents the minimum distance in this space [59].

For a linearly classifiable data set, the number of separating hyperplanes can be more than one. However, one of these planes is called the "optimal hyperplane", which maximises the distance between two classes [60]. SVM determines this optimal separating hyperplane by maximising the margin between the closest points between classes. Points on these boundaries are called "support vectors" and the centre of the hyperplane is considered the optimal separation line [61].

SVM can also combine multiple binary classifiers to obtain a multiclass classifier. This process is formulated by (4).

This organisation aims to more clearly express the basic operation and key concepts of SVMs

$$f(x) = \omega^T x + b = 0, \tag{4}$$

where ω is a weight vector of size N and b bias is used to determine the position of the separating hyperplane. SVMs can face two scenarios depending on whether the data can be linearly separated or not [62]. Figure 4 shows that although there are many planes between two classes, there is only one separating hyperplane that maximises the margin between the classes. The SVM classifier determines the separating hyperplane and the optimal hyperplane that maximises the margin between the closest training samples using (5) [63]:

$$\begin{cases} \min \dfrac{\|\omega\|^2}{2}, \\ y_i\left(\omega^T x_i b \geq 1\right) i = 1,2,3,\ldots\ldots, M. \end{cases} \tag{5}$$

If the data cannot be separated linearly, then the linear separation method may be insufficient. To address this situation, a penalty parameter C and freedom variables ξ_i are added to the expression in (6). The penalty parameter C is used to increase the overall validity of the model and prevent overfitting, while ξ_i variables manage errors by measuring the distance of data points from the classification boundary.

The optimisation problem (6) is solved with these additions to obtain the optimal discriminating plane. This optimisation process is used in cases where data cannot be linearly separated to find the best discriminating plane, thus providing a more effective separation between classes [64]:

$$\begin{bmatrix} \min f[\omega,\xi] = \dfrac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{M}\xi_i \\ subject\ to\ y_i\left(\omega^T x_i + b\right) \geq 1 - \xi_i, \quad \xi_i \geq 0 \end{bmatrix} \tag{6}$$

The binary problem can be transformed into a quadratic optimisation problem as specified in (7). In this transformation, α represents the Lagrange multipliers and K represents the kernel function. The quadratic optimisation problem, with the use of Lagrange multipliers and the kernel function, offers a more efficient method to find the optimal plane that can discriminate

$$\begin{bmatrix} \max \ \sum_i \alpha_i + \dfrac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j K\left(x_i, x_j\right) \\ subject\ to\ \sum_i \alpha_i y_i = 0,\ 0 \leq \alpha_i \leq C,\ i = 1,\ldots\ldots, M \end{bmatrix}. \tag{7}$$

Data sets of two classes cannot always be separated linearly. In this case, they can be moved to a high-dimensional space by projecting the data sets into a feature space, denoted Φ_i. This method is expressed by a kernel function K, which is used to compute the inner product of the feature vectors. In particular, the data are processed by the inner product of feature vectors, denoted as $\Phi_i(x_i)$ and $\Phi_i(x_j)$. In this way, when the data are moved into a high-dimensional space, they become linearly separable. The kernel function K ensures the linear separability of the data when performing this transformation.

Although there are various kernel functions, the most widely used is the radial basis kernel function. The mathematical expression of this function is given in (8). The radial basis kernel function is a particularly effective method for ensuring linear separability of data sets in high-dimensional spaces

$$K\left(x_i, x_j\right) = \exp\frac{-\left\|x_i, x_j\right\|^2}{2\gamma^2}. \tag{8}$$

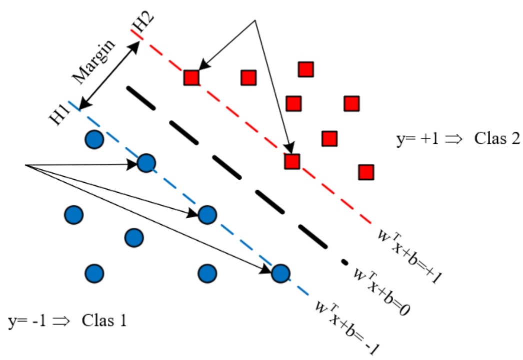


Fig. 4. Linear separation of two classes.

In (8), γ is the width parameter of the radial basis kernel function. The performance of the SVM depends on the parameters γ and C in the case where the radial basis kernel function is used. The γ parameter affects the complexity of the data distributions in a high-dimensional feature space, i.e., higher γ values can separate data points more closely, while lower γ values provide a more general separation. The C parameter balances the classification accuracy with the complexity of the model; a high C value makes the model more accurate, while a low C value creates a more general model. With the addition of the kernel function, the decision function is organised as in (9)

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{n} a_i y_i K\left(x_i, x\right) + b\right). \tag{9}$$

There are two commonly used methods for classification with more than two groups: one-to-one comparison (OvO) and one-to-one versus other (OvA). OvO is a machine learning method in which each class is compared individually with all other classes. In this approach, each class is individually evaluated against each other class. The OvA method is a comparison method in which each class is considered together with all other classes. In this method, a class is evaluated collectively against all other classes, and thus the distinction between classes is examined in a broader context.

III. EXPERIMENTAL SETUP

One of the important problems encountered in pistachio cultivation is that the shells of some products are not open. This is a factor that directly affects the quality and marketability of products. While closed shell pistachios are not preferred by consumers because it is difficult to access their contents, open shell pistachios provide a great advantage in marketing because they are ready for consumption. Figure 5 shows a visual representation of open and closed shell pistachios.

Open shell pistachios are suitable for direct consumption, as they do not require any processing before being offered to the consumer. This gives open shell pistachios a higher value in the market. Since closed shell pistachios are not suitable for consumption without processing, such products are more difficult to market and usually have to be sold at a lower price.

Therefore, distinguishing between open and closed shell pistachios is an important grading problem for both producers and marketers. Accurate and fast sorting of open and closed shell pistachios can improve both product quality and the marketing process. This classification process will increase productivity and minimise economic losses in the agricultural sector.

This important classification problem will be solved using mel frequency cepstrum coefficients (MFCCs) and support vector machines (SVMs). MFCC is a powerful feature extraction method that is used to analyse the frequency components of audio signals. The sound signals generated by pistachios hitting a metal surface will be analysed using MFCC and the features of each pistachio will be extracted and stored in a database.

These data will then be classified using SVMs. SVM is effective machine learning for high-dimensional data and classification. By learning the differences between the audio signals of open and closed shell pistachios, SVM will be able to predict with high accuracy to which class the new pistachios belong to.

By combining these methods, a system will be developed that can automatically determine whether pistachios are open or closed shell. This system will reduce the workload of producers and marketers, increase productivity, and increase economic gains by providing quality control in pistachio production.

Fig. 5. Closed and open shell pistachios.

During the classification process, an experimental setup was built to record the sound of open and closed pistachios hitting a smooth metal plate. This experimental setup was carefully designed to ensure accurate recording and analysis of sound signals. The experimental setup consists of specific components, as shown in Fig. 6.

The experimental setup consists of a styrofoam box (part 1) with dimensions of 50 cm × 40 cm × 25 cm. This styrofoam box was used to minimise environmental noise and to ensure clearer recording of audio signals. The pistachios placed in the box are allowed to free-fall from part 2 in a sequential manner. These free-falling pistachios hit the metal plate (part 3) located at the bottom of the box. The metal plate generates sound signals from the impact of the pistachios.

These sound signals are recorded by a carbon microphone (part 4). Thanks to its high sensitivity, the carbon microphone accurately detects and records the sound signals. The recording is performed using the MATLAB Analogue Input Recorder and a sampling frequency of 44100 Hz. This high sampling frequency enables for detailed recording of audio signals. The recordings are stored on a laptop (part 5) and kept for analysis.

Sample pistachios that hit the metal plate are stored in the storage section (part 6) after the experiment. This section ensures that the pistachios are collected in an organised manner and stored for future use. The experimentally acquired audio signals from open and closed shell pistachios are stored in different databases to be used for classification.

This experimental setup makes it possible to accurately and reliably record the sound signals to distinguish between open and closed shell pistachios. Thus, detailed and precise data sets are obtained to be used in the classification process.

MFCCs and SVMs were used for feature extraction and classification. This process was carried out to accurately analyse and classify the audio signals of open and closed shell pistachios.

In the feature extraction stage, the MFCC method was preferred. MFCC allows for a detailed analysis of the frequency components of audio signals and is widely used in many audio processing applications such as speech recognition. In this study, MFCC is used to extract features from audio signals of both open and closed shell pistachios. For both types of pistachios, 50 samples each were used. These samples provided enough data for the identification and analysis of different features.

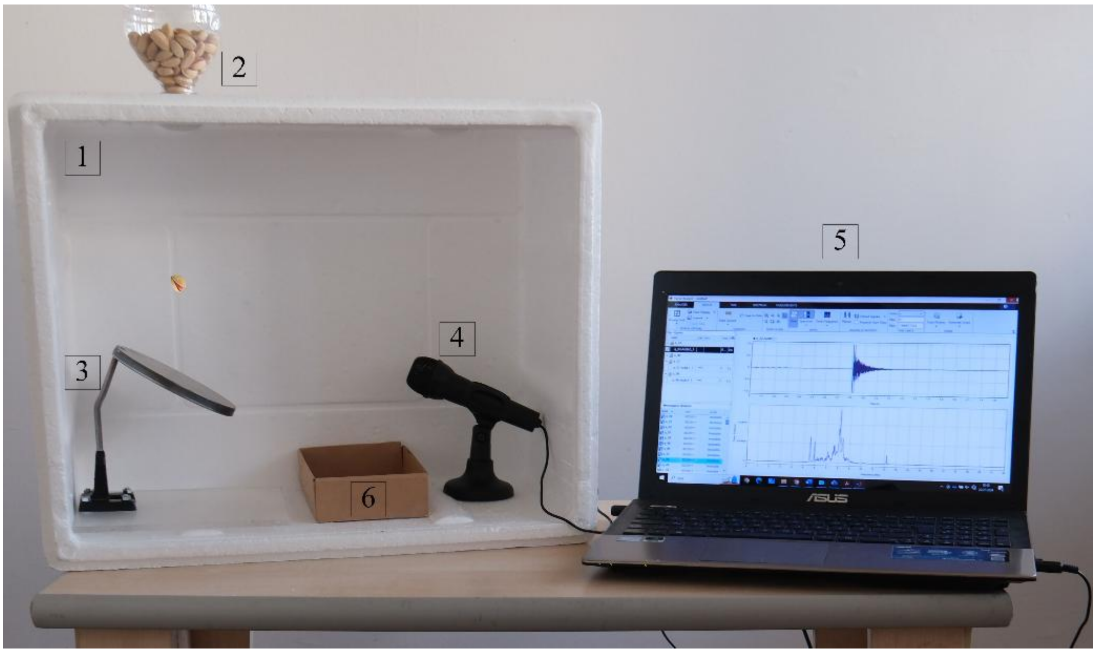


Fig. 6. Schematic of the pistachio classifier based on acoustic emissions.

Some of these samples were randomly selected for training and others for testing. The training set was used in the model learning phase and helped it learn the features of the different classes. The test set was used to evaluate the performance of the model. Training and test sets were created by randomly selecting the data, thus increasing the generalisability of the model.

In the classification phase, SVMs were used. SVM is a machine learning algorithm that gives effective results in high-dimensional data sets and is frequently preferred in classification problems. In this study, SVM is used to classify open and closed shell pistachios based on audio signals. SVM created a classification model using the data in the training set, and this model was tested on the data in the test set.

As a result, feature extraction with MFCCs and classification with SVMs were successfully performed on the audio signals of open and closed shell pistachios. These methods provided high accuracy and reliability in analysing and classifying audio signals. The random selection of training and test sets increased the generalisability of the model and allowed effective results to be obtained in different data sets.

IV. EXPERIMENTAL RESULTS

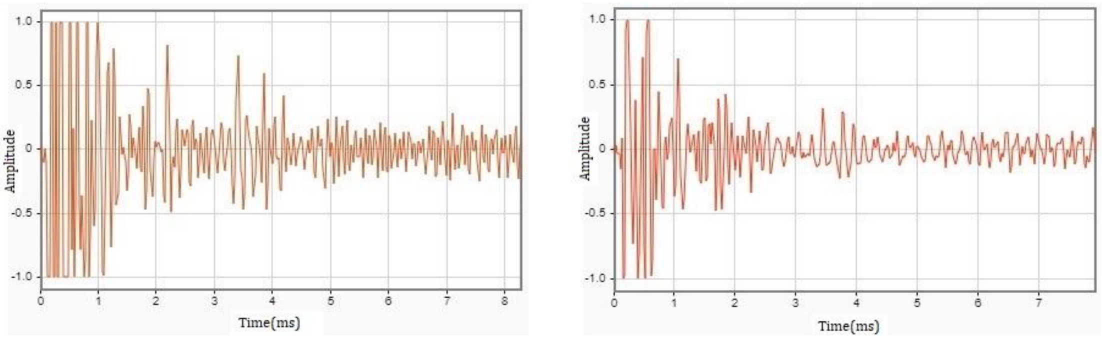
The time-amplitude plots and power spectra of the sound signals generated when open and closed shell pistachios hit the metal plate were analysed in detail. Figure 7 shows the time-amplitude plots of these signals. Time-amplitude plots show the change of the signal over time and its amplitude levels. However, there is no clear distinction between open and closed shell pistachios in this graph. Time-amplitude plots show that both types of pistachios have similar waveforms during impact.

On the contrary, the power spectrum analysis presented in Fig. 8 reveals the frequency components of the signals. The power spectrum shows the energy distribution of a signal as a function of frequency and identifies the different frequency components. In this analysis, there are significant differences between open and closed shell pistachios. In the power spectra of closed shell pistachios, there is a higher energy density in certain frequency components, whereas in the power spectra of open shell pistachios, this density varies. These frequency components play an important role in the classification process.

Figure 9 details the results of the data obtained with open shell pistachios. The results of the data obtained with open-shell pistachios are more balanced and result in fewer errors compared to those of the data obtained with closed shell pistachios. This indicates that open shell pistachios provide more consistent and reliable results in analysing audio signals. As shown in Fig. 9(a) and Fig. 9(b), the reason for the lower optimisation performance of the audio signals recorded with open shell pistachios is that these signals have higher frequency components.

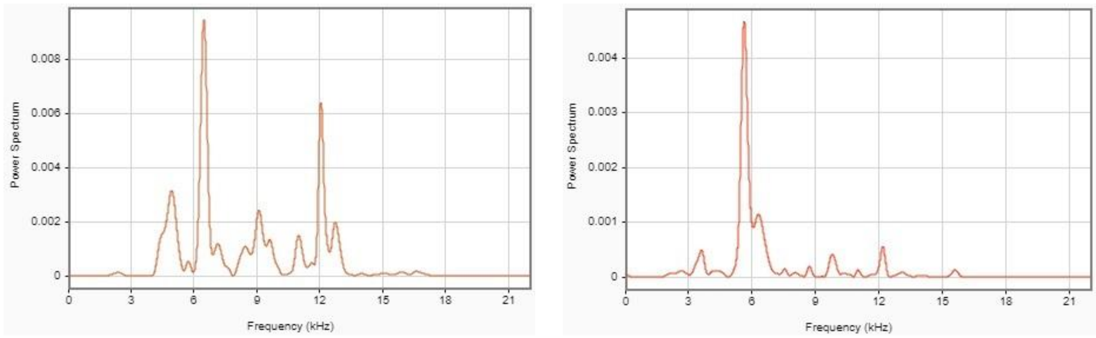
The fact that open shell pistachios have higher frequency components indicates that the signal is more complex and has an energy distribution in a wide frequency range. This leads to more data, and therefore less error in the classification process. On the other hand, the power spectra of closed shell pistachios are dominated by lower frequency components and these signals are concentrated in a narrower frequency range.

In conclusion, the time-amplitude plots and power spectra of the sound signals generated by the impact of open and closed shell pistachios on the metal plate were analysed and it was found that the differences in the frequency components of these signals play an important role in the classification process. These analyses are the basis for improving the accuracy and reliability of classification using mel frequency cepstrum coefficients (MFCCs) and support vector machines (SVMs). These methods will contribute to improving the quality quality and marketing strategies of the product in pistachio cultivation.



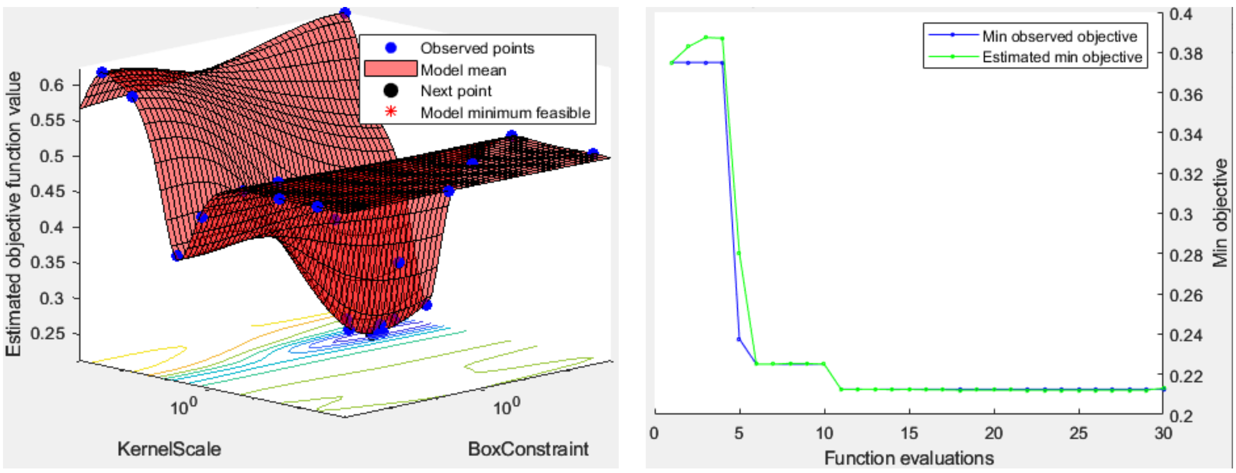
(a) (b)

Fig. 7. Time-amplitude graph for any of the recorded sound signals for: (a) Open shell pistachio; (b) Closed shell pistachio.



(a) (b)

Fig. 8. Power spectrum graph of recorded audio signals for: (a) Open shell pistachio; (b) Closed shell pistachio.



(a) (b)

Fig. 9. (a) Objective function model; (b) Minimum objective vs. Number of function evaluations.

In this study, the best classification model is developed using the Bayesian optimisation process. Bayesian optimisation is a powerful method used to optimise the hyperparameters of machine learning models. In this process, different combinations of hyperparameters are evaluated to determine the best performing model. Figure 9 shows in detail the optimisation process for the best classification model using a typical combination of inputs and the kernel function of the radial basis function (RBF).

Figure 9(a) shows the minimum objective function value and the number of functions. This graph shows how the objective function changes during the optimisation process and how many different combinations are evaluated to get the best result. The minimum objective refers to the hyperparameter settings that minimise the classification loss. The graph shows how the objective function improves and reaches the minimum value at each step of the optimisation process. In this process, many different combinations of hyperparameters were tested to find the best performing settings.

Figure 9(b) shows the observed minimum objective value and the minimum objective value that provides the best prediction. The graph shows the relationship between the minimum objective function value obtained during the optimisation process and the prediction model that provides this value. The minimum observed objective value represents the lowest loss value obtained at the end of the optimisation process. This value matches the minimum objective that provides the best prediction and achieves fewer classification losses. In other words, this graph shows that the best performing model is obtained at the end of the Bayesian optimisation process.

Table I gives the parameters and statistical information of the SVM model. Here, the cross-validation error rate shows that the model performs well on the data set and has a high generalisation ability.

TABLE I. PARAMETERS AND STATISTICAL INFORMATION OF THE SVM MODEL.

Multiple SVM Method	One-vs-One (OvO)
Kernel Function	Radial basis function
Box Constraint	73.275
Kernel Scale	14.528
Cross Validation Error Rate	0.125
Number of Input Data	2
Number of Output Data	1
Number of Training Data	80
Number of Test Data	20

In this study, the classification of each sample was performed 40 times to avoid affecting the classification process by randomness. These repetitions were done to improve the accuracy and reliability of the model. When the classification process is repeated for each pistachio sample, the effect of different variations and possible noise is minimised, resulting in more consistent results. This was an important step to improve the generalisability and classification success of the model.

The classification results for open and closed shell pistachios are shown as examples in Figs. 10 and 11. These figures provide a visual representation of how well the model can classify both types of pistachios. Figure 10 shows the classification results for open shell pistachios and Fig. 11 shows the classification results for closed shell pistachios in detail.

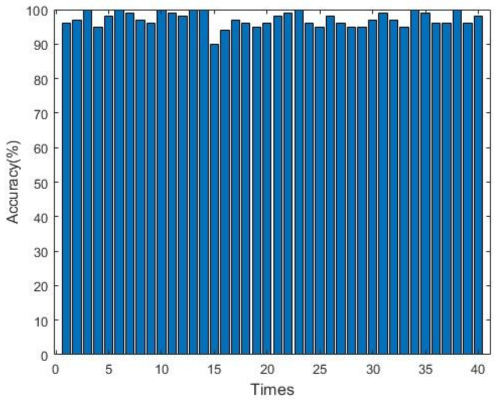


Fig. 10. Results of the open shell pistachio classification.

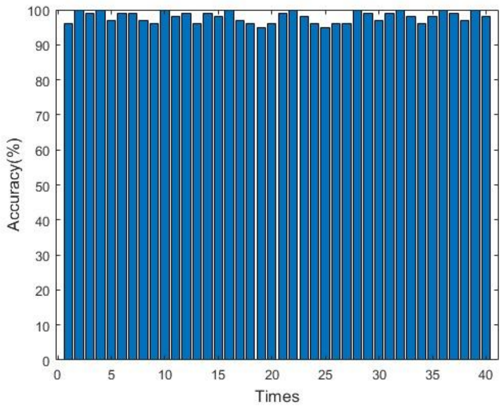


Fig. 11. Results of the closed shell pistachio classification.

Open shell pistachios were detected with an accuracy rate of approximately 97.2 %. This high accuracy rate shows the success of the model in analysing the audio signals of open-shell pistachios and classifying them accurately. When the characteristic features and frequency components of open shell pistachios were accurately identified, the model was able to distinguish such pistachios with high accuracy.

Pistachios with closed shells were identified with an accuracy of more than 97.95 %. The classification of closed-shell pistachios has a slightly higher accuracy rate than that of open shell pistachios. This can be explained by the fact that the sound signals from closed shell pistachios are perceived by the model as more prominent and distinctive features. The model showed superior performance in the classification process by detecting the frequency components and signal features of closed-shell pistachios with higher accuracy.

As a result, the classification of each sample was repeated 40 times in this study, improving the accuracy and reliability of the model. Open shell pistachios were detected with 97.2 % accuracy, and closed shell pistachios were detected with over 97.95 % accuracy. The results presented in Figs. 10 and 11 demonstrate the ability of the model to successfully classify both types of pistachios. These high accuracy rates prove the efficiency and reliability of the pistachio classification process. The results of this study will make significant contributions to improving quality control processes and increasing production efficiency in the agriculture and food industry.

V. CONCLUSIONS

In this paper, an innovative percussion-based system is proposed to detect the open and closed state of pistachios by combining Mel frequency cepstral coefficients (MFCCs) and support vector machine (SVM). MFCC is a popular method for feature extraction by analysing the frequency components of audio signals. In this study, feature extraction is applied by paying attention to the frequencies of human perception, thus capturing the most important frequency components of audio signals.

In the proposed method, SVMs are used to classify open shell and closed shell pistachios. In particular, a machine learning algorithm called the “fit support vector machine” (FITCSVM) is preferred. This algorithm is a classification method that provides fast and effective results on large data sets. The samples used were divided into two categories, open shell and closed shell pistachios, and the classification operations on these samples were performed with high accuracy rates.

Training sets and test sets were obtained from audio signals selected after applying MFCC to pulse-generated audio signals. In this process, each pistachio sample was impacted against a metal plate and the resulting sound signals were recorded and the frequency components were extracted by applying MFCC to these signals. Then, using these frequency components, the classification process was performed with SVM.

Experimental results show that the proposed method can classify open and closed shell pistachios with high accuracy rates. Open shell pistachios were detected with an accuracy rate of 97.2 %, while closed shell pistachios were detected with an accuracy rate of over 97.95 %. These high accuracy rates prove the effectiveness and reliability of the proposed method.

One of the most important advantages of the proposed method is that it can achieve high-accuracy classification results without the need for additional equipment. Using only a carbon microphone and MATLAB software, this classification process provides a simple and cost-effective solution. This approach has significant potential to improve quality control processes and increase production efficiency in the agriculture and food industry.

In conclusion, the percussion-based system proposed in this paper by combining MFCC and SVM was successful in detecting the open and closed state of pistachios with high accuracy rates. With its simple and cost-effective structure, this system can be widely used in industrial applications. The results obtained can be considered as an important step in improving quality control processes in the agricultural sector and automating product classification processes.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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