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RESEARCH ARTICLE

THE DETECTION OF EGGSHELL CRACKS USING DIFFERENT CLASSIFIERS

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ABSTRACT

Chicken eggs, which are widely consumed in daily life due to their rich nutritional values, are also used in many products. The increasing need for eggs must be met quickly for various circumstances. Eggs are subjected to various impacts and shaken from production to packaging. In some cases, these effects cause an eggshell to crack. While these cracks are sometimes visible, they are sometimes micro-sized and cannot be seen. The cracks on the egg allow harmful micro-organisms to spoil the egg in a short time. In this study, acoustic signals generated by a mechanical effect to the eggs were recorded for 0.2 seconds at 50 kHz sampling frequency using a microphone. To determine the active part in the collected acoustic signal data, a clipping process was implemented by a thresholding process. Thus, the exactly correct moment of mechanical contact on the eggshell was easily detected. After passing the determined threshold value, statistical parameters such as min, max, difference, mean, standard deviation, skewness and kurtosis were extracted from the data obtained, and 7-dimensional feature vectors were created. Finally, the Common Vector Approach (CVA) is applied on the extracted feature vectors, 100% success rate has been achieved for the test data set. The ANN and SVM classifiers in where the same feature vectors are treated were used for the comparison purpose, and exactly the same classification rates are attained; however, the less number of eggs are tested with the ANN and SVM classifiers in the same amount of time. With the proposed mechanical system and classification methodology, it takes about 0.2008 seconds to determine whether the shells of eggs are cracked/intact. Therefore, the proposed combination of the feature vectors based on statistical features and CVA as a classifier for the detection of cracks on eggshells is notably appropriate especially for industrial applications in terms of speed and accuracy aspects.

Keywords: Egg, Eggshell, Common Vector Approach, CompactRIO

1. INTRODUCTION

Egg has become a widely consumed food in the daily diet of people due to its low price and rich nutritional value. Cracks may occur in eggshells during the production or shipping processes. This problem can be resulted in substantial economic losses for egg industry because several harmful bacteria may get into the egg through the cracked shell. An infected egg can also pose an important problem in terms of food safety and human health [1-4]. Detecting and separating the cracks on eggshells are important both for commercial and human health considering the above-mentioned issues.

Egg cracks were attempted to be detected using images taken with the aid of a camera [5]. Several image processing and pattern recognition methods have been applied to eggs under a condition of illuminating light source [5–14]. As a result of these studies, it was observed that the cracks on eggshells were detected with a success rate of more than 90% using several computer vision methods. However, it was reported that both the structural defects on eggshells and the incorrect adjustment of illuminating light source cause a problem in detecting cracks by computer vision methods [15]. These methods are also unable to determine micro cracks. It was reported that 100% success rate can be achieved as a result of the clarification of the cracked area by applying negative pressure to egg for the detection of micro

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cracks with computer vision [16-19]. However, these methods are not suitable for applicability to industry because of both the complexity and slowness issues.

Another method employed in the literature for the detection of eggshell cracks is acoustic signal analysis [20]. This method consists of performing a mechanical contact on eggshells, collecting the acoustic signals resulting from mechanical contact, applying various signal processing and feature extraction methods, and finally, classification. The studies performed in [20-29] reported that the detection of cracks on eggshells was succeeded with at most 98.9% accuracy with acoustic signal analysis and proposed classification methods.

In this paper, the acoustic signal generated by a non-destructive mechanical contact on eggshells was recorded for 0.2 seconds durations with the help of a microphone at a sampling frequency of 50 kHz. In clipping of the active part in the recorded acoustic signal, a 0.75V threshold value was preferred. Thus, the precise accurate moment of mechanical contact on a shell can be easily detected. Statistical features were used to reduce the size of the data signals and to determine the effective parameters from the thresholded data signals. By evaluating the min, max, difference, mean, standard deviation, skewness, and kurtosis values obtained from thresholded acoustic signals, 7-dimensioned feature vectors were extracted. Finally, different classifiers are applied to the feature vectors to determine whether an eggshell is cracked or intact.

2. MATERIALS and METHODS

2.1. Experimental Setup

The block diagram of the experimental setup consisting of power supply, control and amplifier circuit, CompactRIO (cRIO), egg support, and mechanical unit for data collection, analysis, and visualization is given in Figure 1. The components are described in detail in the following sections.

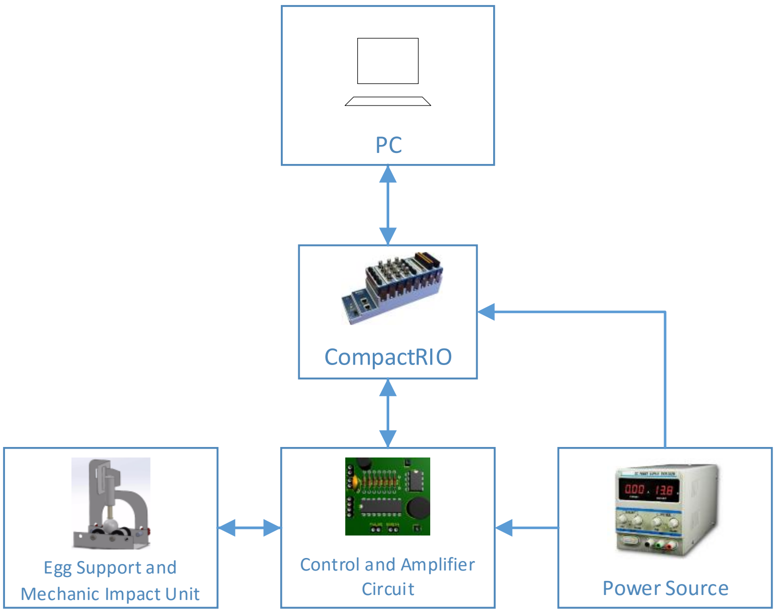

Figure 1. General block diagram of the experimental setup.

2.1.1. CompactRIO

CompactRIO (cRIO) is an application-oriented industrial controller with modular units manufactured by National Instruments (NI) [30]. In this paper, the NI-9215 analog input module and NI-9375 digital input-output module were used together with cRIO 9074. Technical data of cRIO are given in Table 1.

Table 1. Technical data for CompactRIO

Operation Voltage	+19V DC to 30V DC
Processor Speed	400 MHz
Memory	256 MB
FPGA	Xilinx Spartan-3 2M FPGA
Communication Support	Ethernet and RS232
Number of Modular Units	8 Unit

2.1.2. Egg support and mechanical impact unit

Figure 2 shows the general view of setup for the egg support and mechanical impact unit. The egg support unit is the unit on which the egg to be tested is positioned. The mechanical impact unit applies the mechanical impact to the egg and receives the acoustic signal.

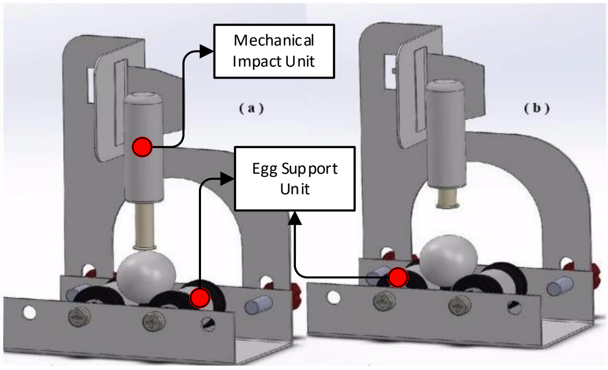

Figure 2. General view of the egg support unit and the mechanical impact unit; (a) the hitting position of the unit to an egg, (b) the starting position of the unit.

The mechanical impact unit consists of a cylindrical outer part on which a coil is wound and a movable cylindrical inner part with a small magnet inside. The movement of the inner part is provided by changing the voltage polarity of the coil wound on the outer part. With this movement, acoustic signals were created as a result of a mechanical impact that is sufficient to generate a mechanical vibration on the egg and does not damage the eggshell. This process is illustrated in Figure 2.

2.1.3. Control and amplifier circuit

The electronic board is designed using L293D and LN358N ICs. With the L293D IC, the mechanical impact unit is driven and the LN358N IC is used to amplify the acoustic signal resulting from the mechanical impact. Electronic card layout is given in Figure 3.

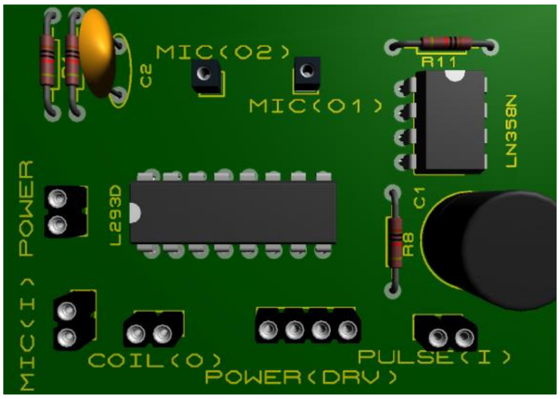

Figure 3. Control and amplifier circuit

2.1.4. Data acquisition program

To create the data set, a data acquisition program was created using the LABVIEW [31] functional blocks, and its screenshot is given in Figure 4. The user interface of the program given in Figure 4, starting with pressing the "get data" button and ends with the acquisition of acoustic data resulting from the mechanical impact applied to the egg, based on the specified sampling time.

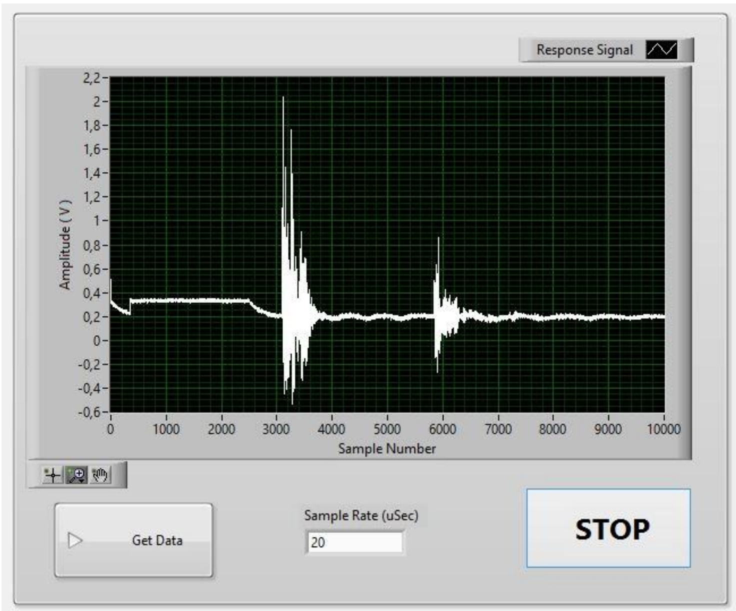

Figure 4. Data acquisition program

2.2. Creating the Feature Vector

There are some noises in the raw signals received for 0.2 seconds at 50 kHz sampling frequency via our data acquisition program. Raw signals exceeding a threshold value of 0.75V, which is determined by trial/error methodology, are gathered to detect the data at the moment of mechanical impact on the eggshell, thereby the noisy part can be discarded. Therefore, data signals which have 680 samples are collected. As a result of the examination of these signals obtained from cracked/intact eggs, it was observed that the signal was stable after approximately this amount of data. Then statistical features were extracted to obtain the feature vectors to be fed to the classifier in order to determine cracked/intact eggshells. A 1x7 dimensional feature vector was constructed using the minimum value, maximum value, difference, mean, standard deviation, skewness, and kurtosis parameters. The equations for statistical features are given in Table 2 [32].

Table 2. Statistical features and their equations.

Feature	Symbol	Equation
min	F_1	$min\{X_1, X_2, X_3, , \ldots X_n, \}, 1 \leq n \leq N$
max	F_2	$max\{X_1, X_2, X_3, , \ldots X_n, \}, 1 \leq n \leq N$
Difference	F_3	$F_2 - F_1$
Mean	F_4	$\frac{1}{N}\sum_{n=1}^{N} X_n$
Standard deviation	F_5	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}(X_n - F_4)^2}$
Skewness	F_6	$\frac{1}{(N-1)(F_5)^3}\sum_{n=1}^{N}(X_n - F_4)^3$
Kurtosis	F_7	$\frac{1}{(N-1)(F_5)^4}\sum_{n=1}^{N}(X_n - F_4)^4$

2.3. Common Vector Approach (CVA)

One of the significant subspace methods used in the 1-dimensional pattern recognition problems is CVA [33-36]. The main goal of CVA is to eliminate the differences in a pattern class and to find a single vector that has the unchanging common properties of that class. The CVA is examined in two different cases according to the relationship between the number of feature vectors in training set of a class and the size of feature vectors. These cases are called as insufficient data and sufficient data cases. In the case of sufficient data used in this study, the number of feature vectors (m) belonging to a class is greater than the feature vector dimension (n) ($m > n$). In this case, the common vector belonging to a pattern class is found using the within-class covariance matrix. Let the column wise feature vectors in the training set of a pattern class are $\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_m$, respectively. In the sufficient data case realization of CVA, first of all, the covariance matrix belonging to a pattern class is calculated as follow:

$$\mathbf{\Phi} = \sum_{i=1}^{m}\left[(\mathbf{a}_i - \mathbf{a}_{ave})(\mathbf{a}_i - \mathbf{a}_{ave})^T\right] \tag{1}$$

Here, $\mathbf{a}_{ave}$ is the average vector of the feature vectors belonging to a class in the training set of the pattern class and $\mathbf{\Phi}$ shows the within-class covariance matrix belonging to that pattern class.

The eigenvalue-eigenvector decomposition of the within-class covariance matrix is performed, and then, n eigenvalues greater than zero value are obtained. These eigenvalues are sorted in descending order.

The largest k eigenvalues among the eigenvalues are chosen with the help of the following inequality [37]:

$$\frac{\left(\sum_{j=k+1}^{n} \lambda_j\right)}{\left(\sum_{j=1}^{n} \lambda_j\right)} \leq Y \tag{2}$$

Where k is the number of largest eigenvalues chosen; λ_j is the eigenvalues, and Y is the fixed percentage value to be used in the eigenvalue selection. If Y = 5.58 %, a good performance is obtained while retaining a small proportion of the variance present in the original space. Y = 5.58 % is the average rate for eigenvalues of within-class covariance matrices calculated in each cross-validation step. The value of k was equal to four for each class (intact or cracked egg), and it can also be specified from the point where the eigenvalues of the training data start for varying slowly upon plotting of the eigenvalues in descending order. k eigenvectors corresponding to k eigenvalues of the computed within-class covariance matrix span the difference subspace of that pattern class. The remaining $(n-k)$ eigenvectors will span the indifference subspace of that pattern class. In this circumstance, the projection ($\mathbf{a}_{i,dif}$) of any $\mathbf{a}_i$ feature vector belonging to a pattern class into the difference subspace of that pattern class is calculated as follow [38]:

$$\mathbf{a}_{i,dif} = \sum_{j=1}^{k} \left[(\mathbf{a}_i^T \mathbf{u}_j) \mathbf{u}_j \right] \tag{3}$$

Here, $\mathbf{u}_j$ are the eigenvectors spanning the difference subspace of that pattern class. The common vector belonging to that pattern class is calculated with the help of the mean vector as follows:

$$\mathbf{a}_{com} = \sum_{j=k+1}^{n} \left[(\mathbf{a}_{ave}^T \mathbf{u}_j) \mathbf{u}_j \right] \tag{4}$$

After the calculation of the difference/indifference subspaces and the common vector, the training phase of CVA is completed. In the test phase of CVA, the $\mathbf{a}_x$ vector, which will be classified in the pattern test set, is tested using the following decision criteria and assigned to the appropriate class:

$$S^* = \underset{1 \leq C \leq S}{argmin} \left\| \left[\sum_{j=k+1}^{n} \left(\mathbf{a}_x - \mathbf{a}_{ave}^C \right)^T \mathbf{u}_j^C \right] \mathbf{u}_j^C \right\|^2 \tag{5}$$

Where S is the number of classes, $\mathbf{u}_j^C$ are the eigenvectors spanning the indifference subspace of the class C, $\mathbf{a}_{ave}^C$ represents the average vector of the class C, and S^* represents the class to which the unknown $\mathbf{a}_x$ vector was assigned as a result of the testing process.

3. RESULTS and DISCUSSION

A total of 10000 samples of data signal for each egg during 0.2 seconds at 50 kHz sampling frequency were obtained using the system in Figure 2. A data set was created using 60 different eggs with intact shells and 59 different eggs with cracked shells. The raw data signals collected from the eggs with intact and cracked shells are shown in Figure 5. The change of the direction of magnetic field in coil in mechanical impact unit is constituted by the change of the polarity of voltage applied, and thus, the pin in the coil can move out and in easily. There is also a ball at the end of the pin. Acoustic signals are collected through the microphone installed inside the pin.

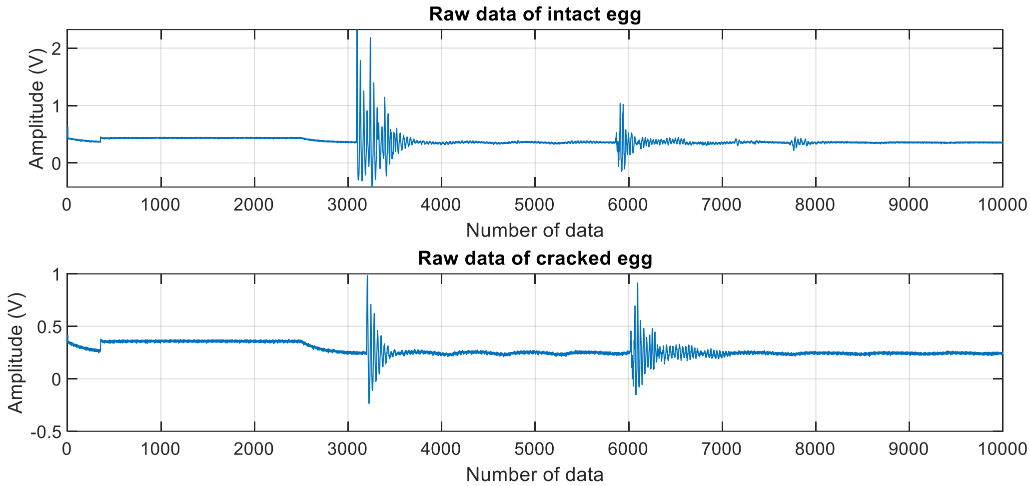

Figure 5. Raw data of eggs with intact and cracked shells

The effect at the moment of contact of the pin on the eggshell and also the effect occurred when it moves back to its starting place are observed in the recorded acoustic signal. A threshold value was determined to obtain useful data from the mechanical impact on the eggshell. In this way, only the acoustic signals generated by the egg were separated from the noisy raw signal generated by the mechanical impact unit and the environment. Starting from the first data point exceeding the 0.75V threshold value from the raw data, 680 data samples were selected. The examples of the selected signal partitions can be seen in Figure 6.

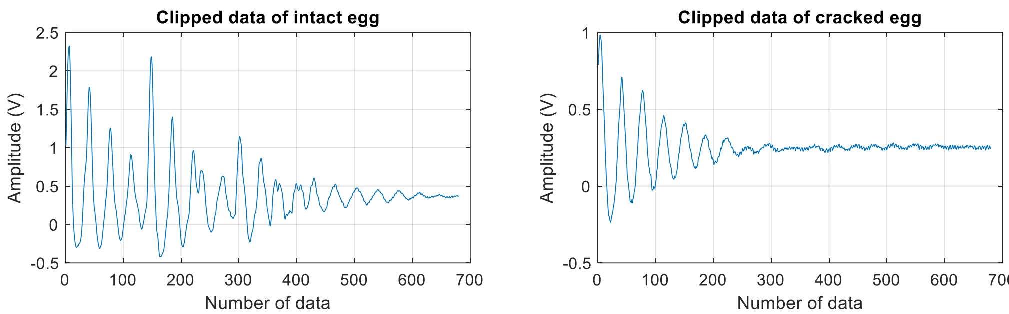

Figure 6. Examples of clipped acoustic signals (each one has 680 samples)

As a result of the mechanical effect, the oscillation of the acoustic signal formed in an intact egg shell is higher than that of in a cracked egg, and the resulting oscillations were damped in a longer time. In the acoustic signal received from an egg with a cracked shell, the oscillation was less and it was damped in a shorter time than an intact egg. The reason for this outcome is that the ball at the end of the pin oscillates more in an egg whose shell is intact.

Feature extraction based on statistical parameters was implemented to feed more effective data to the classifier. Thus, 7-dimensional feature vectors are extracted for each acoustic signal, and then were treated as classifiers. In Table 3, randomly selected feature vectors from the test data of eggs with cracked/intact shells are given.

Table 3. The randomly selected feature vectors of eggs with cracked/intact shells

	Min	Max	Difference	Mean	Standard Deviation	Skewness	Kurtosis
Intact	-0.3619	2.3400	2.7019	0.3862	0.3986	1.5679	7.6146
	-0.2644	2.2696	2.5341	0.4506	0.3574	1.5852	8.1705
	-0.5024	2.8389	3.3413	0.4148	0.5241	1.5083	6.8850
Cracked	-0.1424	1.0062	1.1487	0.3035	0.1165	1.1644	14.5977
	0.0913	0.9922	0.9008	0.4475	0.1016	1.1130	12.1071
	-0.3326	1.0897	1.4223	0.1696	0.1499	1.2530	12.5297

The change in the parameters of maximum, difference, standard deviation, skewness, and kurtosis is seen more effectively among the feature vector parameters obtained by processing an acoustic signal from a cracked/intact egg. The CVA classifier was trained using feature vectors of 10 intact and 10 cracked eggs randomly selected from the data set consisting of 60 eggs with intact shells and 59 eggs with cracked shells (Table 4).

Table 4. Training/test data and performance of the CVA classifier

	Intact	Cracked	Success
Training	10	10	100%
Test	50	49	100%

When the literature studies on the detection of cracked/intact eggshell by processing the acoustic signal resulting from the mechanical effect on an eggshell are examined, there is not an available data set on this subject, and each researcher creates his/her own data set. Ketelaere et al. (2010) applied Fast Fourier Transform (FFT) to the acoustic signal recorded from eggshells at 50 kHz sampling frequency. The Pearson correlation coefficients of the processed acoustic signal were found and the coefficients exceeding over a threshold value are determined; finally, the cracked/intact conditions of shells were determined with a 90% success rate [39]. Deng et al. (2010) applied Continuous Wavelet Transform to the acoustic signal recorded at 22.05 kHz sampling frequency. They achieved a 98.9% success rate by estimating with SVM using different combinations of wavelet-based extracted features [22]. Sun et al. (2013) transferred the data from the time domain recorded with 38 kHz sampling frequency into the frequency domain with FFT. A calibration model was created and five features were extracted from magnitude response of each signal in the frequency domain. If the value of three or more features exceeds their critical values, the eggshell is considered to be intact, otherwise is cracked. While the average performance rate was 98.05%, this method requires less time than 10ms to determine the state of the shell from raw data signal of an egg [40]. In this study, an acoustic signal was collected from an eggshell in 0.2 seconds at 50 kHz sampling frequency. Approximately 0.212 seconds in ANN, 0.205 seconds in SVM, and 0.2008 seconds in CVA are required for processing raw data signals. The consumed time values comprise of the extraction of a feature vector, and performing the estimation process by a classifier. Thus, the shell of 16981 eggs is tested with ANN for an hour. In the same amount of time, additional 579 eggs with SVM and 947 eggs with CVA can be tested. The performance rate for CVA, ANN, and SVM classifiers in where the same feature vectors are treated was determined as 100%. Since the classification process for an egg can be done in totally about 0.2008 seconds, the combination of the feature vectors based on statistical features and CVA as a classifier is considerably suitable for industrial applications.

The 5-fold cross validation technique was performed to evaluate the performance of the feature vector and the CVA classifier. All egg data were randomly divided into five groups; each one includes eggs with 10 cracked shells and 10 intact shells. While one group of data was used in the training phase of the CVA classifier, the remaining four groups of data were used in the testing process. The performance for each cross-validation step was found to be 100%, therefore, the average testing performance was computed as 100%.

An interface was created with Matlab/GUI to determine the cracked/intact situation in an eggshell collecting/processing/classifying data from the system. By pressing the "Get Data/Analyze" button in Figure 7, the raw data signal taken from an egg is plotted on the graphical display. The raw data signal can be analysed in detail using the tools on the interface. Data is clipped using the threshold value. The feature is extracted and fed to the classifier. At the end of the classification, the decision (either cracked or intact) is printed on the interface and also shown visually on the screen.

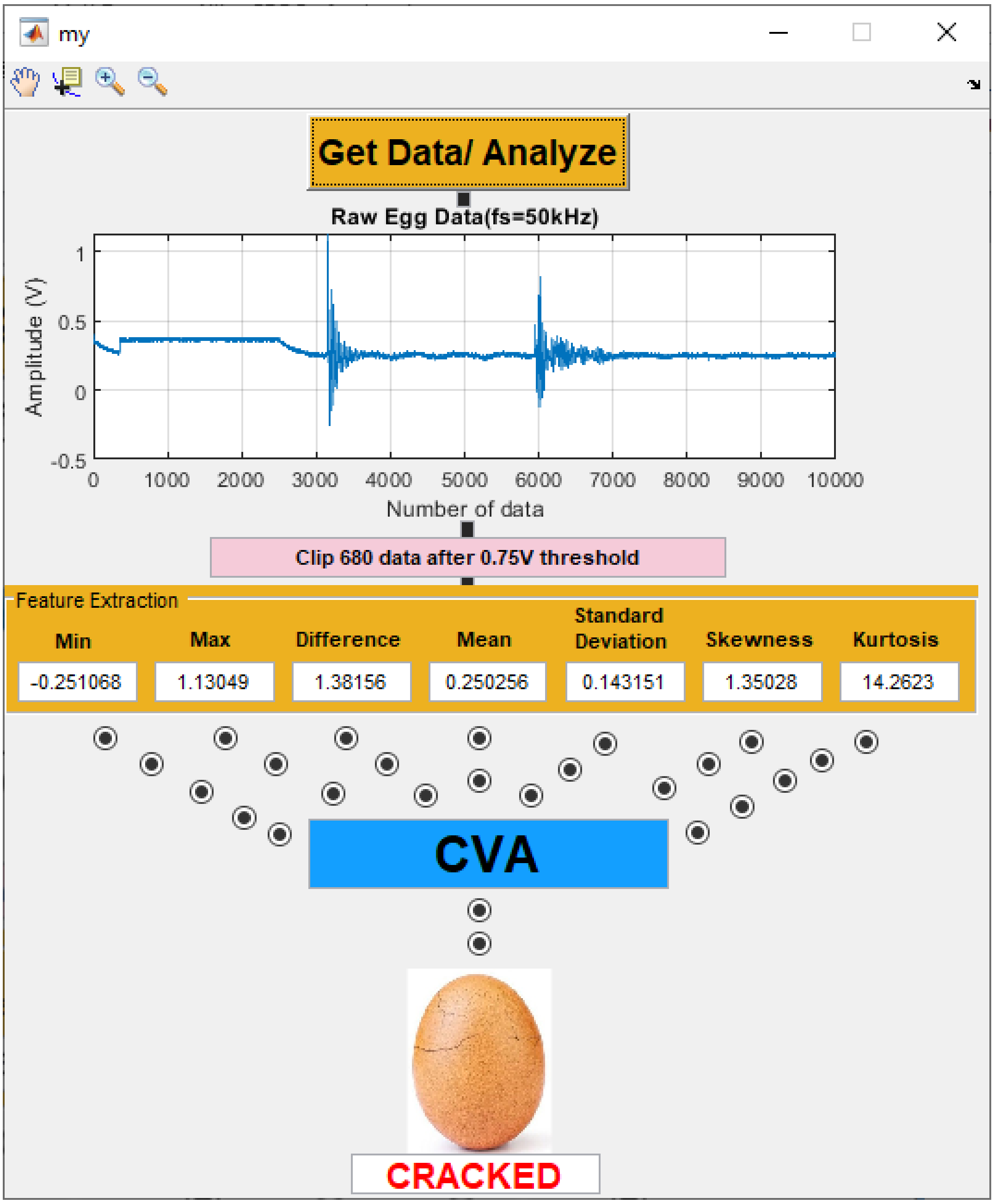

Figure 7. Eggshell control interface

4. CONCLUSION

Chicken eggs are exposed to various impacts and are shaken from the production to the packaging stages and several cracks may occur in their shells. These cracks can be micro-sized and invisible and also cause an egg to deteriorate in a short time. In this study, the acoustic signals generated as a result of the contact made by a mechanical system in a way that it does not damage the eggshell are recorded with a microphone. The active part in acoustic signal was determined by thresholding acoustic signal using a pre-determined value. The statistical features were evaluated, and a feature vector with a size of 1x7 was extracted from each thresholded acoustic signal. For the training of the CVA classifier, 20 data signals, including separately ten feature vectors selected randomly from cracked and intact eggs, were used; and, the other remaining 99 egg data signals in the data set were used in the test process. Although the training process was carried out with a very few data feature vector, all of the test data signals were correctly classified. It takes an average of 0.2008 second for data signal to be retrieved from an egg, pre-processed, and estimated by the CVA classifier. The combination of the extracted feature vector and the CVA classifier are practically suitable for industrial applications due to the speed and accuracy issues for the process of cracked/intact detection of eggshells. Although exactly the same accuracy rates are obtained for CVA, ANN, and SVM classifiers, the less number of eggs are tested with the ANN and SVM classifiers in the same amount of time.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

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