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Artificial Intelligence Based Determination of Cracks in Eggshell Using Sound Signals

Zekeriya BALCI[1], İsmail YABANOVA[*2]

Abstract

Although the egg is a cheap food source, it is one of the valuable nutritional sources for people because of its rich nutritional values. It is also among the most consumed foods in daily nutrition. With the increase in egg production, it is very difficult to collect them with the human power in the egg production farms, to classify them according to their weights and to separate the defective (dirty and broken) eggs. Therefore, the mechanization has become a necessity in large capacity production farms. Cracks and fractures may occur in the egg shell as a result of exposure to external factors such as the transportation of eggs. The cracks or fractures that are formed leave the egg vulnerable to disease-causing micro-organisms. Before the egg sorting and packing, the broken and cracked eggs must be separated. This process is commonly carried out with manpower by which it is very difficult to obtain the necessary efficiency. In this study, the egg crack detection was performed by using Support Vector Machines (SVM) and Artificial Neural Network (ANN). As a result of the application of studied methods, the accuracy values of crack detection process were 0.99 for ANN and 1 for SVM. In addition, a data acquisition and processing program was developed in LABVIEW environment to detect cracks in real time.

Keywords: Cracked egg detection, artificial neural networks, support vector machines, LABVIEW.

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1. INTRODUCTION

Eggs are one of the basic foods preferred by people for their daily nutrition because of their rich nutrient content and low cost for which egg consumption is increasing. With the increase in egg consumption, the capacity increase in egg production farms is unavoidable and many machines have been developed due to increase in high production capacity. These machines carry out processes such as the collection, transport, and classification of eggs according to their weights, sorting of dirt, blood, and condition i.e. broken and cracked, based on some parameters. Cracks and fractures may occur in the egg shell when exposed to physical effects during the harvesting processes such as collection, transportation and packaging. The cracks in the egg shell can make the egg vulnerable to harmful micro-organisms. An infected egg may threaten the health of human beings and eliminate the food safety. In order to eliminate or minimize these problems caused by cracked eggs, it is important to detect and separate the cracked eggs at the production stage [1-3].

Studies for the detection of egg cracks have been focused on acoustic signal processing and image processing methods [4]. Many studies have been carried out for crack detection using acoustic signals from the mechanical effect applied to the eggshell that will not harm the egg. The Pearson correlation coefficient method was used to detect egg crack detection with 90% accuracy [5]. Acoustic signals obtained from the egg shell by applying the Support Vector Data Definition method, the egg crack detection was possible with 90% accuracy [6]. Wavelet transform application to acoustic signals obtained from eggshell and trained SVM with these data was reported that a crack detection with 98.9% accuracy was achieved [7]. A similar studied with the same principle of wavelet transform application to acoustic signals obtained from the egg shell the crack detection was reported with 95% accuracy [8]. They also emphasized that there are significant differences between the energy values of the signals in solid and cracked eggs. The transformation of the acoustic signals obtained from the egg into a frequency domain helped determine the cracks in the egg shell with the accuracy of 96.1% using the calibration model method. In another study, [9] reported that they performed cracked egg detection with 90% accuracy by applying Halanobis distance method to acoustic signals that they obtained from egg shells. The feature extraction was applied to acoustic signals obtained from brown and white eggs and examined them in time and frequency space [4]. Using these signals, they have trained the artificial intelligence model.

Another method used in the detection of cracked eggs has been the image processing method. Fang and Youxian [10] stated that they carried out the crack detection process with an accuracy of 88% through the images they obtained from the egg. They reported that they tried to detect cracks by using many image processing methods and that the best method for their studies was the morphological (structural) image processing method. In order to determine micro-cracks a vacuum suction force was applied to the egg by li et al [1] and who stated that micro-cracks in eggshell was detected with 100% accuracy with image processing methods. They also reported that their systems were for a single egg, that the light source had a significant effect on the result, and that the system speed was not suitable for the industry. Omid et al [11] determined egg crack detection using egg images and fuzzy logic method with 94.5% accuracy. Öztürk and Gangal [12] identified the defective and clean eggs by using image processing methods for the detection of dirt and crack in the egg shell with 93% accuracy, 92% of dirty eggs and 88% of cracked eggs.

In this study, crack detection process was performed in real time by using SVM and ANN method by using acoustic signals formed by application of a mechanical impact to the egg shell which does not cause any damage in egg shell. For the training of SVM and ANN methods, 50 cracked and 50 intact eggs were used. The training of ANN and SVM models was realized with 99% and 100% accuracy, respectively. In addition, the trained ANN and SVM models were tested in real time with 40 cracked, 60 intact egg samples, except for eggs used for training, using real-time crack detection program. At the end of the testing procedure, the eggs were classified with the accuracy of 100%. In the literature, it was observed that the signals obtained from the egg shell were transferred to the frequency domain and then the feature was extracted and then crack detection was employed. In this study, the acoustic signals obtained from the egg shell were used without any pre-processing procedure and the crack detection process was carried out successfully.

2. MATERIAL AND METHOD

2.1. Experimental Setup

The experimental setup developed consists of power supply, operational amplifier and control circuit, CompactRIO (cRIO), software for collecting, analyzing and visualizing the data. Figure 1 shows the system developed for application. The following sections describe the components in detail.

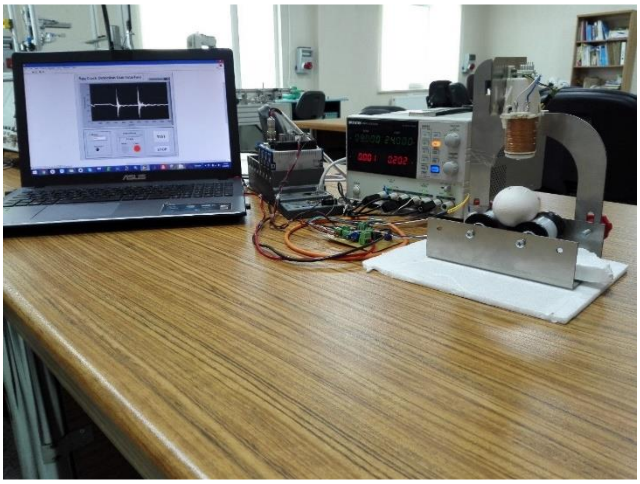

Figure 1 General view of system components

2.1.1. CompactRIO

The production of CompactRIO National Instruments (NI) is a configurable industrial controller for application with modular units [13],[14]. In this study, NI-9215 analog input module and NI-9375 digital input output module was used with cRIO 9074. cRIO technical specifications are given below.

• Operating voltage between + 19V DC and 30V DC.

• 400 MHz processor speed.

• 256 MB internal memory.

• Xilinx Spartan-3 2M FPGA.

• Ethernet and RS232 communication support.

• 8 modular units.

2.1.2. Egg Support Unit and Mechanical Impact Unit

The egg support unit and the mechanical impact unit where the egg is positioned are given in Figure 2. With this unit, a mechanical impact is applied to one egg placed on the rollers and the sound signals generated by this effect are collected with a microphone.

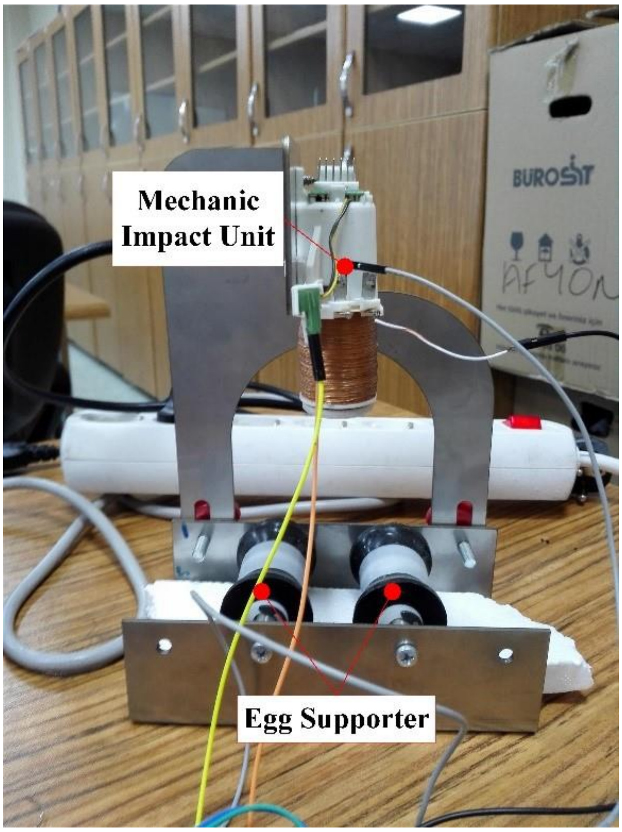

Figure 2 General view of egg support unit and mechanical impact unit

The mechanical impact or unit consists of a hollow tube on which a coil is wound and a cylindrical hammer moves inside the tube. This moving part enables the formation of acoustic signals by a soft collision that will not damage the egg's shell, and this event is illustrated in Figure 3.

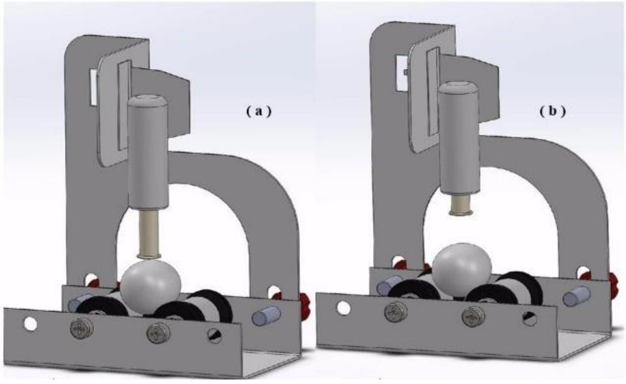

Figure 3 Impact position on egg (a), starting position (b)

2.1.3. Signal Amplifier and Control Circuit

In order to strengthen the acoustic signals obtained from the egg shell and to control the mechanical effect unit, an electronic card was designed using the L293D driver IC, the LN358N amplifier IC and the passive circuit elements required for the circuit is shown in Figure 4.

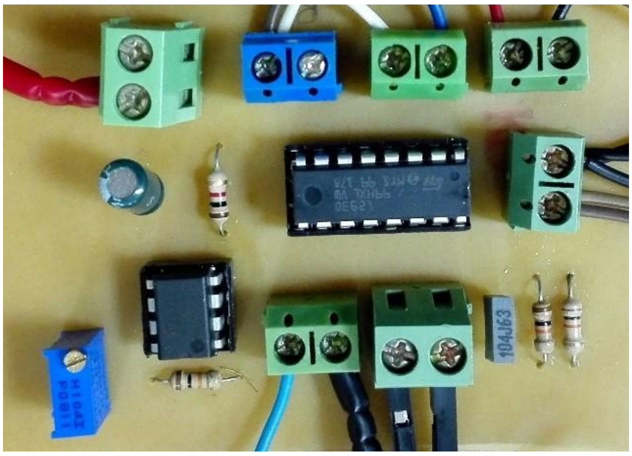

Figure 4 Signal amplifier and control circuit

2.2. Classification Method

2.2.1. Artificial Neural Networks

ANNs can be defined as structures created by human learning, the ability to hide the information learned, and the ability to mimic skills such as the ability to predict new data encountered by using learned knowledge [15-17].

ANN structures are systematic structures consisting of parallel processing capability and parallel connection process elements, connections belonging to the network and information stored. A simple ANN model is given in Figure 5. ANN entry and values of results are trained with the known training set. Following the training process, they are tested with the value of the output value they produce compared to the input value that they did not observe before and with the control of the error value according to the output value. ANNs have the advantages of being fault tolerant, learning by using examples, applicability to complex problems, compliance with real - time problem solutions [16-18].

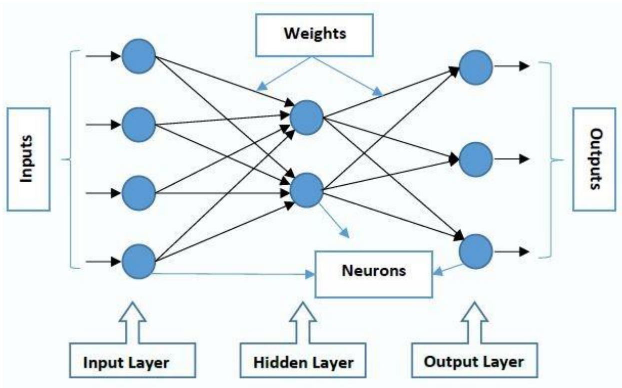

Figure 5 A simple artificial neural network sample diagram [15]

2.2.2. Support Vector Machines

The SVM aims to find the right to distinguish the problem samples into the classes they belong to, and based on statistical learning methods, which has been proposed by V. Vapnik as a theory in the 1960s [19]. Considering that each problem data is represented as a point in the data space, one can refer to the purpose of the SVM as to create a distinction plane that can distinguish the points of different classes [20, 21]. In Figure 6 (a), it can be seen that the two different classes can be drawn correctly. However, the SVM is to find the optimum (Fig. 6 (b)) separator plane that can distinguish the main objective problem data at the maximum accuracy level [22]. SVM have been applied in many areas such as the classification of facial expressions, classification of types of deterioration in power quality, asynchronous motor broken rotor rod fault detection, face recognition, voice recognition [23-25].

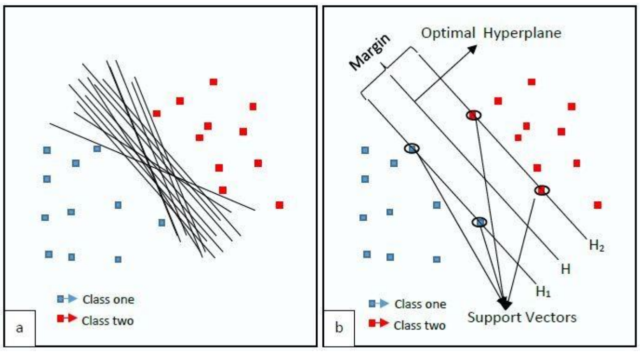

Figure 6 Lines that can separate samples (a) and optimal line (hyperplane) (b) for SVM [20], [27]

2.3. Developed Programs for Crack Detection

LABVIEW software, which is marketed as an object-oriented development environment by NI has been used for computerization of acoustic signals obtained from egg shell, visualization of triggering and manipulation of control signals [26]. For crack detection, a program has been developed primarily for data collection from the system. The data obtained from this program were developed in artificial intelligence training programs and training was provided for ANN and SVM. Then a program for real-time crack detection was developed. These programs are given under sub-headings.

2.3.1. Data Acquisition Program

The data acquisition program developed in the LABVIEW environment is given in Figure 7 to create the training data set which is necessary for the training of SVM and ANN structures created in this study. When the “Get Data” button is pressed, a mechanical impact is applied to the egg based on the sampling time specified and the resulting sound signal is received.

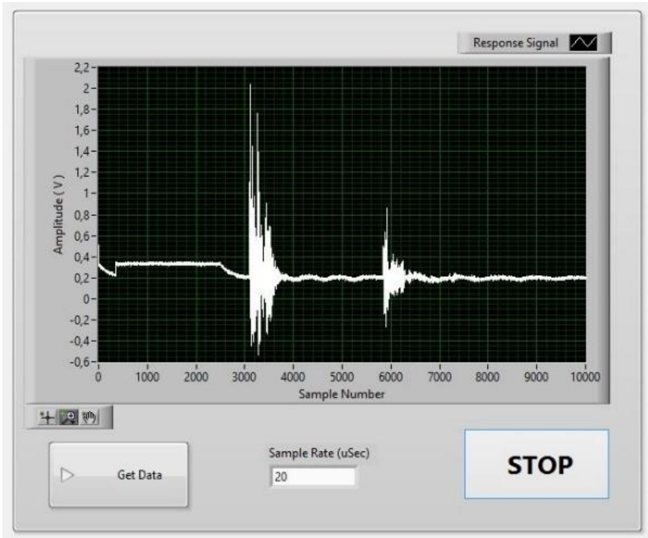

Figure 7 Data acquisition program developed in LABVIEW environment

2.3.2. AI Training Programs

For the training of ANN and SVM artificial intelligence models, LABVIEW program and AML (Analytics and Machine Learning Toolkit) tools developed by NI for LABVIEW software environment were used [27]. The programs prepared for the creation and training of ANN and SVM artificial intelligence models are shown in Figure 8 and Figure 9 respectively. By entering the desired parameters into these programs, the accuracy values generated by the training of the data set can be seen and ANN and SVM models can be saved.

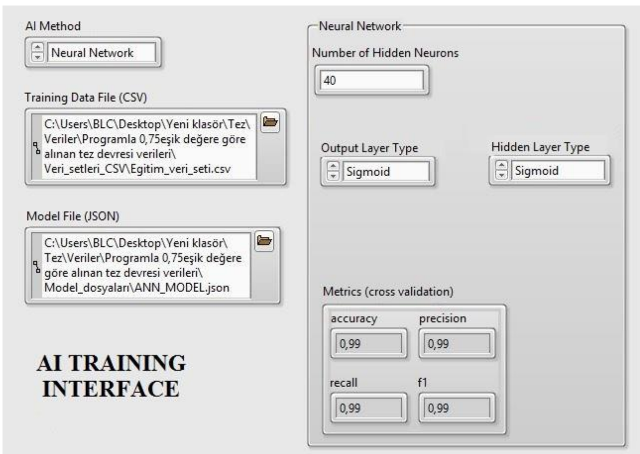

Figure 8 ANN training program

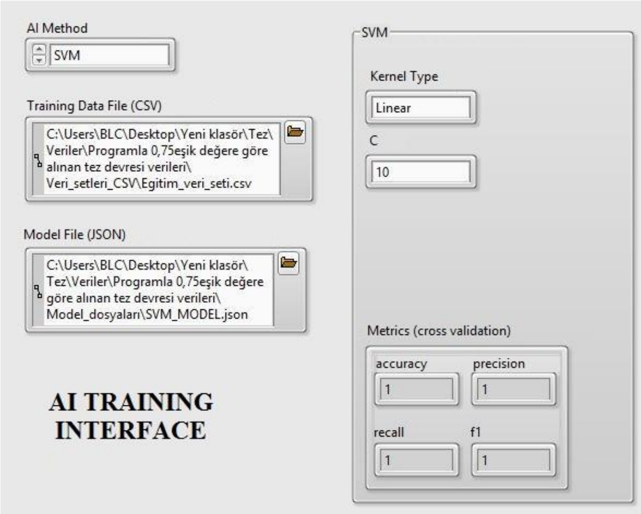

Figure 9 SVM training program

2.3.3. Real Time Crack Detection Program

The program developed in order to realize egg crack detection in real time using the trained SVM and ANN models is given in Figure 10. By pressing the "RUN" button, the card which controls the mechanical impact unit sends a signal for the mechanical effect to be performed. As a result of the mechanical impact, the acoustic signals from the egg are transferred to the computer via the experimental device. For cracked eggs, the mechanical impact was applied to cracked area or the vicinity of the cracked area. The response signal obtained during this process is shown in the "Response Signal" graph screen given in Figure 10. Then, the data belonging to the egg is obtained from the response signal according to the values entered in the threshold value and the number of data to be received in the program in Figure 10. Data is received according to threshold value, and then the egg response data is passed through the program to the selected classification method and, the classifier gives the class label for the egg and the process for an egg is completed.

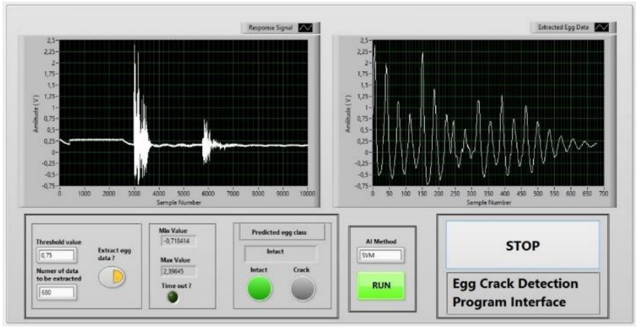

Figure 10 Real-time egg crack detection program

3. RESULTS AND DISCUSSIONS

In this study, the primary aim is to classify intact and cracked eggs correctly. For this purpose, a total of 200 eggs were purchased from the same supplier: M (53-63 g) quality class 90 cracked and 110 intact. A sample image of the purchased intact and cracked eggs is shown in Figure 11 and the response signal curves from the eggs are given in Figure 12.

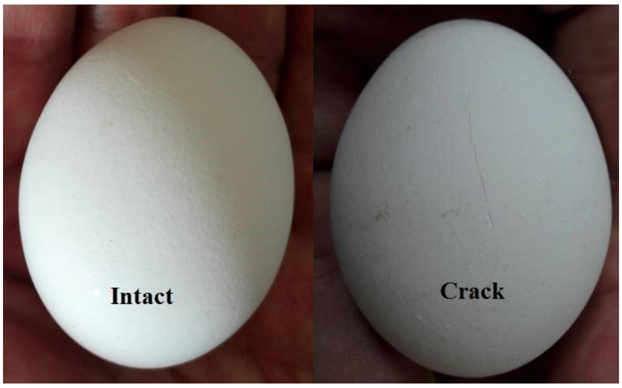

Figure 11 Sample egg images belonging to groups (intact and cracked)

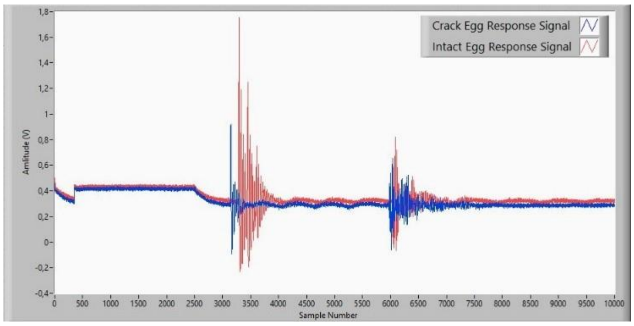

Figure 12 Response signal graphs of intact and cracked egg

Figure 11 shows the crack on the egg, however, some eggs may have micro cracks and these cracks are not visible under normal conditions and atmospheric pressure. Figure 13 shows the image of an egg with a micro-crack in its circumference, marked by a yellow line.

Figure 13 Image of the egg under micro-cracking under normal pressure

As can be seen in Figure 13, there is no cracked area on the egg surface under atmospheric pressure prior to any external force or impact applied onto the egg. However, when a squeezing action of hand i.e. an external force is applied to the egg with a micro-crack, the cracked area becomes noticeable as shown in Figure 14. In addition, the fact that micro-cracks cannot be seen under normal pressure may be a problem in machine vision methods [1].

Figure 14 Image of micro-cracked egg under compression

For the training of SVM and ANN, 50 intact and 50 cracked eggs data were obtained with the program given in Figure 7. The data from the eggs were obtained as 10,000 sample points with a sampling frequency of 50 kHz. The response signal obtained from an intact egg is given in Figure 15.

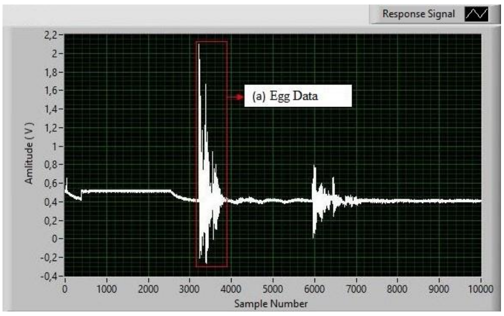

Figure 15 Intact egg response signal graph

In Figure 15, the data of the intact sample egg is indicated by (a). As can be seen in the figure, the response signal received from the egg contains noise signals along with the egg data, and signals from the testing environment. 680 data samples were selected starting from the first data point exceeding the 0.75V threshold value from the raw data. This way, the response signal at 10,000th sample point length is largely free of interference signals and 680 sample point length egg data has been eventually obtained. In addition, the number of entries for the methods to be used for the classification by this process is also reduced. Figure 16 shows the response signal of the egg data cropped according to the threshold value.

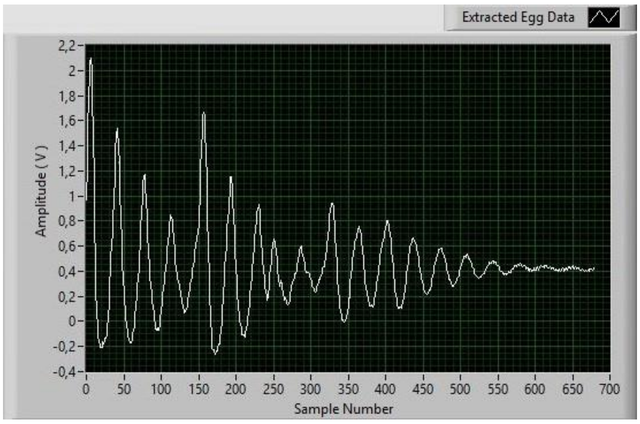

Figure 16 Egg signal obtained according to the threshold value

The data from cracked egg was obtained by applying a mechanical impact force perpendicular to the cracked area or its vicinity. However, sample data were collected away from the crack zone. In Figure 17, a cracked egg is marked with a cracked area and a point away from the cracked zone. Figure 18 is a graph of the signal (1) from the crack region and the signal (2) was obtained from the intact egg and signal (3) was obtained at the point away from the crack region given in Figure 17. On examining the signals from specimens given in Figure 18, the peak values in the response signal obtained from the point (3) away from the crack zone increased relative to the response signal (1) obtained from the crack zone and the duration of the signal is prolonged. In this context, the response signal graph obtained from the distal region was found to move away from the signal curve taken from the fracture zone and close to the intact egg response signal.

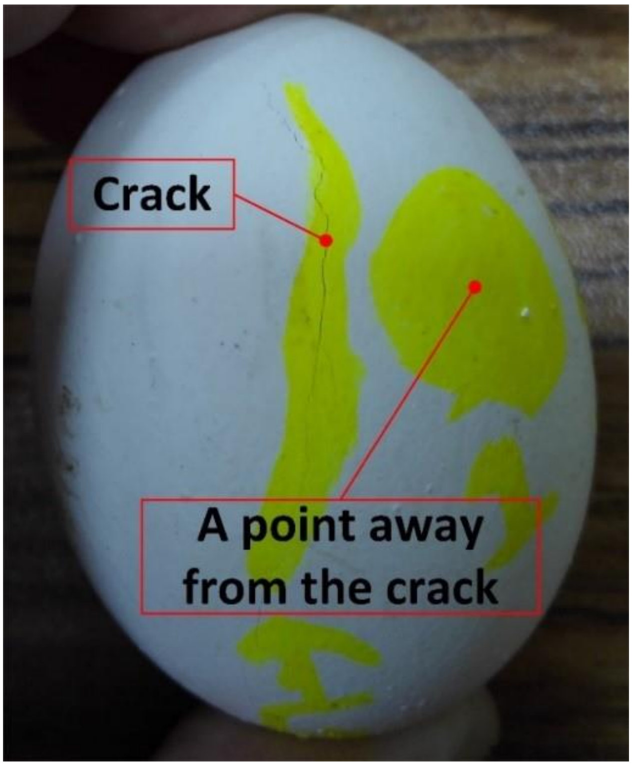

Figure 17 Image of a cracked region of a cracked egg and a point in the distance

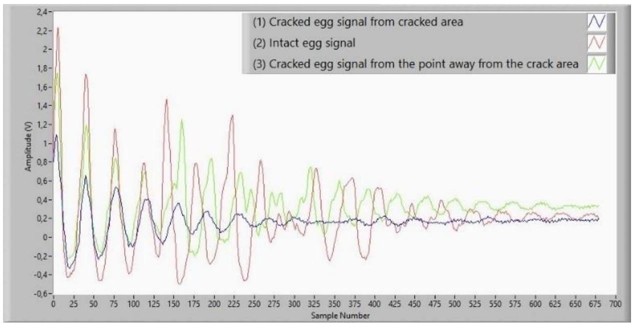

Figure 18 Intact egg and cracked signal from different points of the egg

In order to create the data sets for the training of SVM and ANN models, a total of 100 eggs data were collected, including 50 cracks and 50 intact eggs. The remaining 40 cracks and 60 intact egg samples were separated by the real-time egg crack detection program to further test the SVM and ANN structures. The data set consists of 680 sampling points collected at 20us sampling time. The program developed for the creation and training of ANN model is given in Figure 8. The implemented ANN model is feed-forward neural net that applies gradient descent algorithm which has one hidden layer. As can be seen from the figure 8, there are 40 neurons in the hidden layer in the ANN model and sigmoid function was chosen as the activation function for the hidden and the output layer. The program algorithm divides the training data into three and allocates one-third of the remaining data for the test for training. The training process was carried out with a value of 0.99 as shown in the “Cross Verification Values” section of the given program. As can be seen in the figure 9, the linear function is selected as the kernel function for SVM structure and c, the value of the penalty parameter, is 10. The accuracy of the SVM model in the training process was 1.

For the real-time egg crack detection program in Figure 10, ANN and SVM models were tested in real time with 40 cracked, 60 intact egg samples. The test results showed that SVM and ANN models were found to correctly classify all 100 eggs into the classes they belong to and this process was realized in real time. While the estimation result for the ANN egg class was around 120 milliseconds, it was found that the SVM egg class estimation result produced around 20 milliseconds. It was stated that the training process had an accuracy of 1 for SVM and an accuracy of 0.99 for ANN. In this context, it can be claimed that in terms of training success and the duration of production of estimation result, SVM for this study gives better results than ANN.

4. CONCLUSIONS

Eggs are one of the main food sources. Eggs may contain cracks in their shells due to exposure to the processes such as harvesting, transporting and packaging in the egg production farms. The cracks can leave the egg vulnerable to bacteria and harmful microorganisms. In this study, it was aimed to determine the cracks of the eggs by using SVM and ANN artificial intelligence methods. During the formation of SVM and ANN models, 100 eggs were used, 50 of them were intact and 50 of them were cracked eggs. The training process of artificial intelligence methods was 0.99 for ANN and 1 for SVM. These accuracy values were found to be above the studies in the literature. In addition, a real time egg crack detection process in the LABVIEW environment has been developed. With the help of egg crack detection program, using 40 cracked and 60 intact eggs, which were not used in the training of ANN and SVM structures, were tested in real time. As a result of the test procedure, it was seen that eggs were classified correctly by both models. With the program developed within the scope of this study, it was possible to detect egg cracks in real time by the entering the egg data to SVM and ANN models without applying a pre-signal processing method. In addition, in terms of accuracy and the duration of production of the estimation result, it was observed that SVM model gave better results than the ANN model. It was concluded that both models would provide the desired high detection speed criterion easily in industrial applications.

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The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the authors.

Authors' Contribution

The authors contributed equally to the study.

The Declaration of Ethics Committee Approval

This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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