Turkish Journal of Veterinary & Animal Sciences

Volume 48 | Number 3 Article 5

2024

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TÜBİTAK

Turkish Journal of Veterinary and Animal Sciences

http://journals.tubitak.gov.tr/veterinary/

Research Article

Turk J Vet Anim Sci
(2024) 48: 156-164
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doi:10.55730/1300-0128.4349

Application of some artificial intelligence optimization methods to determine the freshness of eggs

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Received: 14.01.2024 • **Accepted/Published Online:** 25.05.2024 • **Final Version:** 05.06.2024

Abstract: Egg quality, can be divided into two groups as internal and external, is evaluated using various methods whether breaking eggs. Image processing makes digital images usable for various purposes such as image compression, image editing, object recognition, face recognition, medical imaging, and many other areas such as the automotive industry. This study aimed to determine the freshness of eggs using different artificial intelligence optimization methods with image processing without breaking the eggs. Artificial neural networks (ANNs), artificial bee colonies, particle swarm optimization, and genetic algorithms were compared using classification coefficients. As a result of the study, it was determined that ANNs, GA, PSO, ABC algorithms had R^2 values of 0.9492, 0.14, 0.07, 0.13, respectively, and ANNs could be used to determine egg freshness. According to the results, it has been understood that the most suitable method for determining egg freshness is artificial neural networks which can be effectively used for this purpose and has sufficient accuracy to be transferred to industrial applications.

Key words: Image process, egg freshness, artificial intelligence, storage time

1. Introduction

Eggs are considered an important source of nutrients such as high-quality protein, fats, vitamins, and minerals in human nutrition [1]. Additionally, eggs are an affordable and readily available food item. However, the nutritional value of eggs decreased with prolonged storage time, although their edibility remains preserved. Albumen, the protein-rich white portion, is one of the key factors determining egg quality [2].

Although the quality of albumen can be inconsistent and varies from egg to egg, it is affected by several factors such as temperature, relative humidity, hen age, and storage time [3,4]. One of the most important indicators of egg quality affected by storage conditions and time is the thinning of albumen [5]. When an egg is cracked onto a smooth surface, the egg yolk is typically in a central position surrounded by thick albumen [6–8].

Egg quality is evaluated using various methods, which can be divided into two groups: methods that involve breaking eggs and those that do not. The Haugh unit (HU) is the most commonly used method for measuring egg quality by breaking eggs [9]. This method is based on the relationship between the weight of a sound egg and the height of its albumen, which is measured after the egg is broken. As time passes after an egg is laid, the weight of an unspoiled egg and the viscosity of its albumen decrease due to water loss [10]. Measuring the individual freshness of eggs by breaking them is important, but determining the freshness of unbroken eggs is also important from an economic and consumer standpoint. Freshness can be determined by various measurements made by breaking eggs to determine their freshness. However, egg freshness varies individually due to various factors. Since broken eggs cannot be reused, the determined freshness levels are estimated by generalization. In this case, stale eggs can be considered fresh and fresh eggs can be considered stale. To prevent this situation and prevent economic losses, various studies have been conducted to measure the freshness of unbroken eggs [10–13] including image processing.

Image processing makes digital images usable for various purposes which include image compression [14], image editing [15], object recognition [16], face recognition [17], medical imaging [18], and many other areas such as the automotive industry [19]. Many algorithms can be used for image processing. ANNs are frequently used for image processing. ANNs are an artificial intelligence method designed by taking inspiration from biological neural systems and used to process and model complex data [20].

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ANNs used in image processing provide successful results, particularly in areas such as object recognition and face recognition [21]. They are also widely used in the field of medical imaging [22]. Thanks to their ability to process and learn from large data sets, artificial neural networks are an extremely effective tool in image processing, and they are expected to be used more widely in the future [23].

Genetic algorithm (GA) is a popular artificial intelligence technology used in optimization problems, inspired by natural processes such as natural selection and genetic crossover [24]. GA's use in the field of image processing has also been investigated by many researchers. GA is considered an effective optimization method, especially for feature selection and extraction problems in image processing. Also, GA is unstable to random selection in large datasets [25]. Anai et al. [26] developed a GA-based feature selection method and demonstrated that this method achieved higher accuracy rates in image classification problems. Similarly, Raj [27] developed a Kernel Nearest Neighbour (KNN) based Genetic Algorithm (GA) feature extraction method and reported that this method was effective in brain tumor stages grouping done. GA optimization is completely dependent on chance and probability [28]. GA can also be used in compression problems in image processing. For example, Idrees et al. [29], in a study conducted for image compression, propose a Steady-State Genetic Algorithm (SSGA) based two-stage quantization algorithm for image compression.

GA has also been successfully used in object tracking problems. Hwang et al. [30] proposed a GA-based object tracking method and showed that this method had higher accuracy rates. GA is seen as an effective optimization method for solving different problems in the field of image processing.

Particle Swarm Optimization (PSO) has become popular among nature-inspired optimization methods in recent years. Particle swarm optimization algorithm has inertia in achieving the balance between local search ability and global search ability [31, 32]. The success of PSO can be attributed to its ability to be used in many different application areas and its high performance in image processing.

Another use of PSO is in image-based data compression. Chen et al. [33] compared a Particle Swarm Optimization (PSO) based method with other methods for image compression. Both image encoding and decoding processes have been simulated and the results show that this algorithm is reliable and the reconstructed images are of higher quality compared to other methods. PSO is also used in image classification. In another study, Junior et al. [34] proposed a new algorithm based on Particle Swarm Optimization (PSO) and Convolutional Neural Network (CNN), this algorithm is called PSO-CNN. The proposed algorithm has fast convergence ability compared to other evolutionary approaches. In the image classification application, the algorithm has achieved success in automatically finding deep meaningful CNN architectures. In order for PSO to be used with CNN, a rate operator for direct coding was created with a new strategy.

Artificial Bee Colony Optimization (ABCO) is a nature-inspired optimization method frequently used in image processing in recent years [35]. ABCO is an artificial intelligence method designed by taking inspiration from the food collection behaviour of a bee colony. This method is particularly effective in processing complex and multidimensional data [36]. Different researchers are exploring application areas of engineering, science, and medical with ABC [37]. When used in conjunction with Convolutional Neural Networks (CNNs), frequently used in large training datasets, ABCO exhibits high classification performance [38]. ABCO is also effective in object detection [39]. Effective results of ABCO in image compression have also been observed [40]. ABCO usage is also recommended for feature selection [41].

Karaboğa et al. [42], compared Bee Colony Optimization (ABC) with Particle Swarm Optimization (PSO), Differential Evolution (DE), Evolutionary Strategy (ES), and Genetic Algorithms (GA) on a larger set of numerical test functions. They conducted a study. The results obtained showed that the performance of ABC was at least similar to or better than all these algorithms, and was achieved with a smaller number of parameters. Therefore, it is expected that the use of ABCO in image processing will become more widespread in the future.

The aim of this study is to determine the freshness of eggs stored in the refrigerator for 29 days without breaking them, using image processing methods and artificial neural networks, artificial bee colony, particle swarm optimization, and genetic algorithms.

2. Materials and methods

2.1. Sample preparation

In the study, 50 white eggs laid on the same day and stored at +4° for 29 days were used. A Canon 550D camera was used to transfer egg images to the computer, which were fixed with a tripod. The taken photographs were saved in RGB format with a fixed ISO value and a size of 18 MP. All optimizations were implemented in MATLAB software.

2.2. Preparation of photos

The dirty spots in the black areas behind the eggs in the obtained (Figure 1 (I)) photographs were cleaned using an image processing program (Figure 1 (II)). The cleaned photographs were cropped to a size of 2000 × 200 × 3 pixels (Figure 1 (III)) and reduced to a size of 300 × 300 × 3 pixels using Matlab software.

2.3. Data preprocessing

The data was multiplied with its determinant after being printed in a single row. This resulted in a 3 × 3 color matrix representing the image (Figure 2). The 3 × 3 data matrix was converted into a single-column matrix of size 1 × 9 representing a single column. Thus, the raw data composing the study (29 × 50) is composed of a 1450-column, 9-row matrix.

2.4. Algorithm applications

2.4.1. Artificial neural networks

Artificial neural networks are a type of information processing system that mimics the working and operation mechanism of the nerves in the brain, with the aim of providing abilities such as learning, understanding, analysis, synthesis, and generalization [43]. Artificial neural networks formed by bringing cells together with nonrandom connections with the coming together of neurons and layers are formed. The structures formed by the artificial cells and the layers that they are connected to be designed to receive inputs from the external environment and transmit outputs. All remaining neurons are located in hidden layers and different network architectures can be formed depending on the different connection patterns between the layers. In the early usages of artificial neural networks, it was assumed that the connections were random, and some negative results were encountered [44]. Layering the elements that make up a structure provides great convenience in design, and there are three parts to this layering: input, hidden, and output layers (Figure 3).

2.4.2. Genetic algorithm optimization

Genetic algorithm applies optimization problems through a virtual evolutionary process taking into account Darwin's theory of evolution. In this process, the natural evolution process is mimicked and certain operations are performed. The operations performed in a simple genetic algorithm are selection (copying), crossover, and mutation. Some of the terms used in genetic algorithm are explained below [45].

Individual: It is known as the chromosome in the literature. It consists of the arranged design variables that can be a solution to the problem.

Parent individual: Any individual that undergoes genetic operation to produce a new individual (child individual).

Generation: Any population created in genetic algorithms with the participation of a certain number of individuals to obtain better parent individuals.

Fitness: The measure of design achievement.

Genetic operation: The operations that provide information communication between parent individuals.

In genetic algorithms, each solution is represented by an individual (chromosome) in the generation, and individuals are represented by number sequences.

Genetic algorithms enable the attainment of the best solutions by gradually applying genetic operations to the solution population and generating new generations through search from suitable populations. Most simple genetic algorithms consist of four main operations entitled as selection, replication, crossover, and mutation [46].

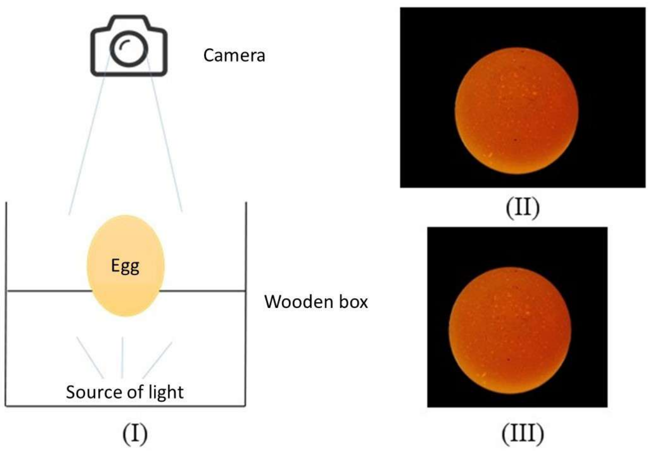

Figure 1. (I) Photo Frame, (II) Cleaned photo, (III) Cropped photo.

$$\begin{vmatrix} R^2 & RG & RB \\ RG & G^2 & GB \\ RB & GB & B^2 \end{vmatrix}$$

Figure 2. Color matrix.

2.4.3. Particle swarm algorithm optimization

PSO, shares many similarities with evolutionary computation techniques such as genetic algorithms. Like genetic algorithms, it begins by working with a population of random solutions and searches for the best solution over a number of generations. However, PSO does not use genetic operators such as mutation and crossover. Instead, it uses possible solutions consisting of various parameter values called "particles" that have a position and velocity vector [47]. These particles move through the problem space by following the best particles obtained thus far. Due to its ease of implementation and quick convergence to acceptable solutions that increased the popularity PSO method [48].

The PSO algorithm starts with all particles randomly placed in the search space, and their positions are updated at each step. These particles move with a certain velocity to continue the search process for finding the best result [49].

2.4.4. Artificial bee colony algorithm

In a natural bee colony, work is done according to a division of labor by the bees. The ability of bees to perform division of labor and to come together for a specific purpose is known as an important characteristic of swarm intelligence. Tereshko [50] proposed food search model consists of three components: food sources, worker bees with tasks and worker bees without tasks. Food sources are known as the sources that bees try to reach to obtain nectar or pollen. The value of a food source depends on many factors such as its variety, proximity to the hive, viscosity of the nectar, and ease of obtaining the nectar.

3. Result

The data was divided into three subgroups as training (70%), validation (15%), and testing (15%). Twenty-nine target values were used along with 1450 input data, and 10 hidden layers were employed. The R^2 values between the estimated data and expected target data were calculated as 0.95 (Figure 4). As a result of the ANN analysis, the storage time was determined.

In the study, 50 iterations, 29 classes, and a population size of 10 were used for the GA method. Along with the optimization by the genetic algorithm, instead of the expected 29 classes, only 10 classes could be formed by GA. The obtained specification coefficient from the GAO classification was 0.14 (Figure 5).

The PSO algorithm used 29 class numbers, 50 particle numbers, and 100 number of iterations. While PSO was expected to divide into 29 classes, PSO could only divide the data into 8 classes (Figure 6). The classification obtained from PSO resulted in a specificity coefficient of 0.07.

The artificial bee colony algorithm was implemented with 29 class number, 20 bees, and 50 iterations. With the applied artificial bee colony optimization, instead of the expected 29 classes from ABC, it was able to create 9 classes (Figure 7). The classification coefficient obtained from ABC was found to be 0.13.

4. Discussion

Artificial neural networks have been used in many optimization problems. Partal and Kişi [51] used ANNs and autoregressive models to predict average hourly wind speeds in the future. They reported that ANNs gave better results than autoregressive models in the evaluation performed. Bolzan et al. [52], attempted to egg hatchability prediction using ANNs and multiple linear regression by using based on data obtained from industrial incubations. It was reported that ANNs gave better results than multiple linear regression which used coefficients determined by the minimum square method. Similarly, our research results suggest that ANNs provide better results compared to other optimization methods.

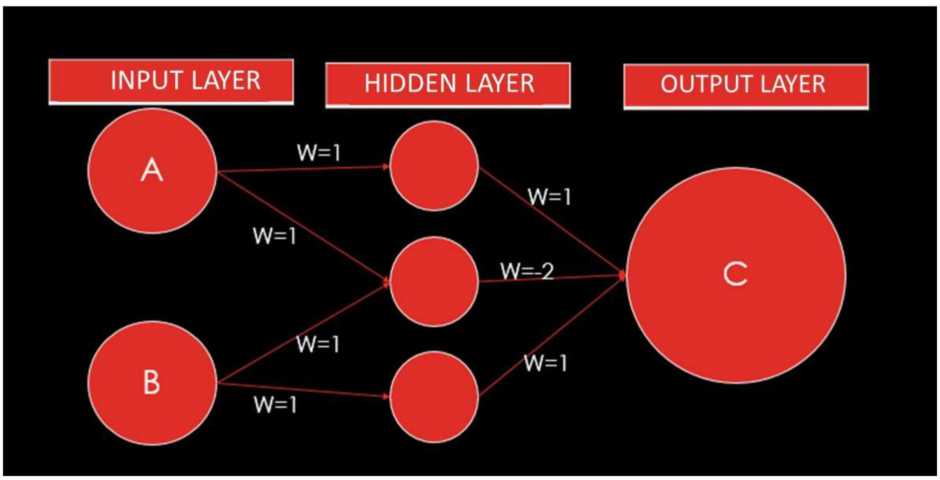

Figure 3. Simple neural network model representation.

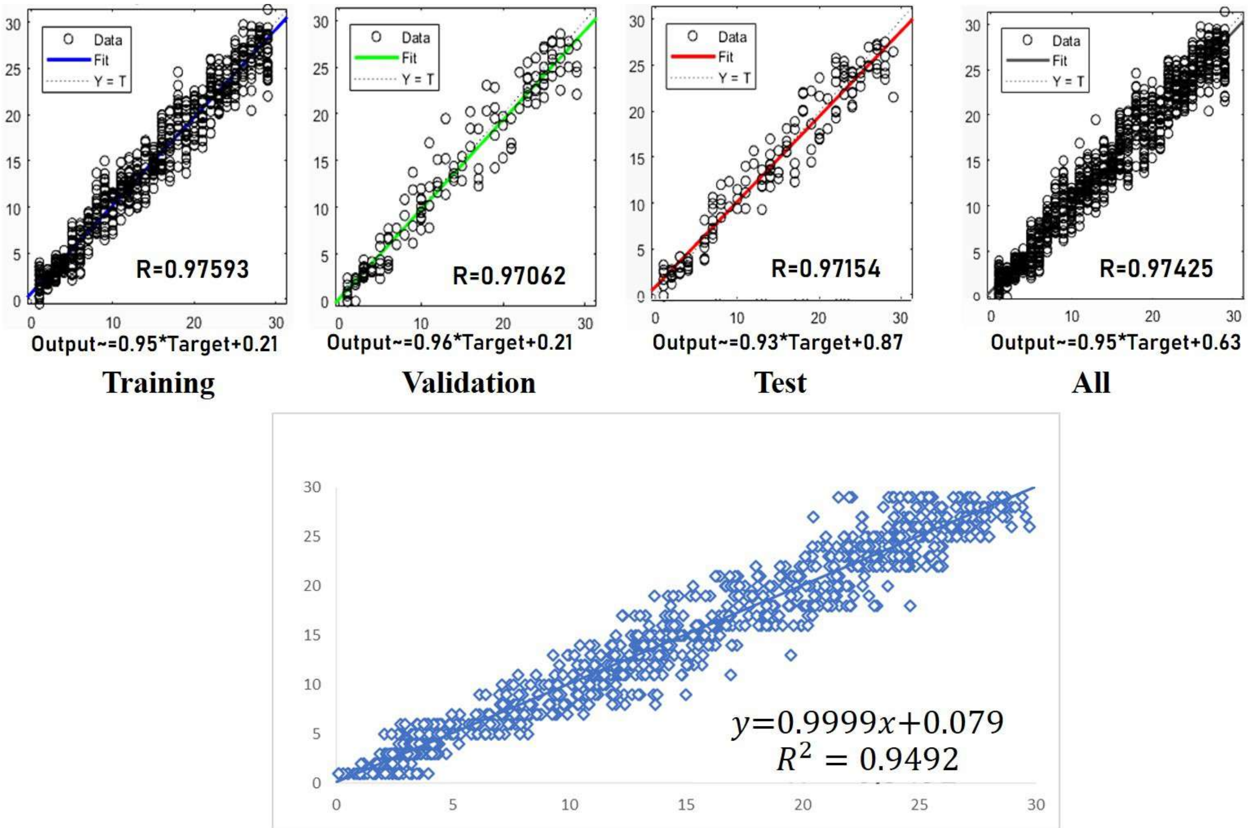

Figure 4. ANN results and prediction graph.

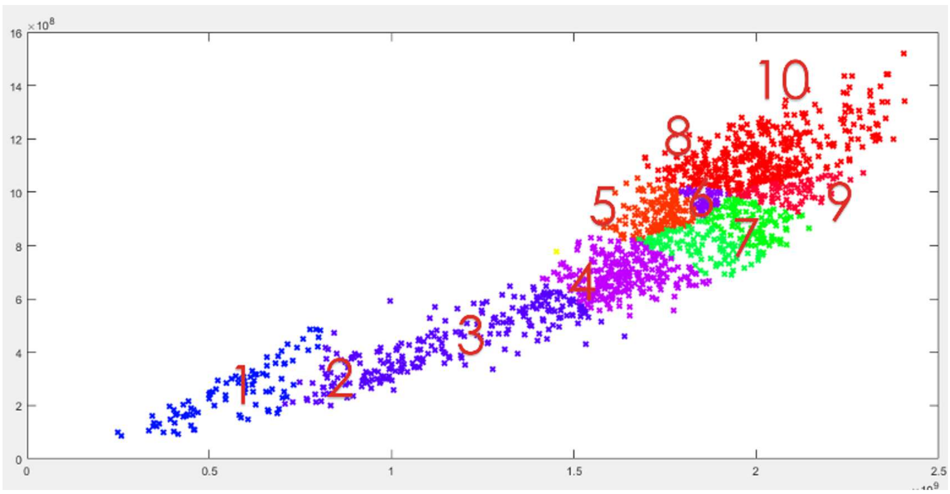

Figure 5. GA prediction graph.

Tozan [53] compared the GA and PSO methods for solving the sensor placement problem. The study reported that the GA method provided better results than the PSO method. On the other hand, it was reported that the local search method improved the PSO method for different terrain types, but not for the GA method. Önder [54] used PSO and GA to optimize vehicle routing problems. In their study, GA and PSO were used together to search for the optimum solution for vehicle routing problems and compared with the current situation. The new model

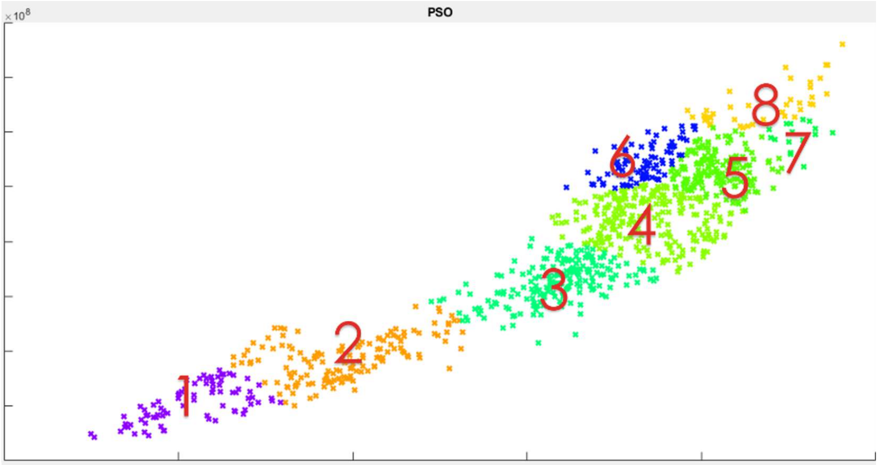

Figure 6. PSO prediction graph.

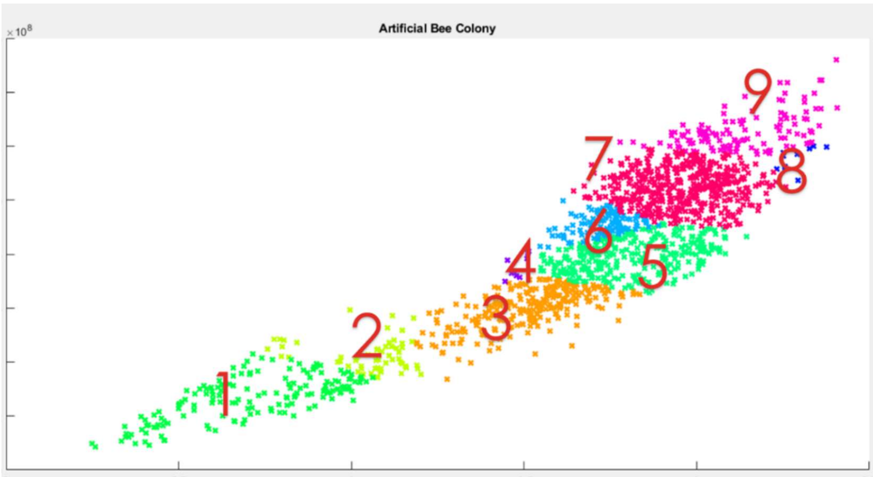

Figure 7. ABC prediction graph.

produced achieved up to 35% improvement. Our research findings suggest that GA optimization is not sufficient for determining the freshness of eggs when color factors are used.

Yakut et al. [55], used PSO and GA methods to predict Türkiye's energy consumption until 2050. In his study, he found the R^2 value to be 93% for PSO analysis and 94% for GA analysis. PSO was determined to have a lower error rate than GA. The PSO model was reported to provide better results than GA. In a study comparing the performance of PSO and GA heuristic algorithm methods [56], the two algorithms were compared. The study concluded that the PSO algorithm provided better results. In our study to determine the freshness of the eggs, it was determined that PSO was not sufficient.

In Türkeli [57]'s study, the Artificial Bee Colony and Genetic Algorithms were employed to determine the optimal designs of partially prestressed concrete beams in terms of cost. The study found that the average values of the optimal costs obtained with the Artificial Bee Colony Algorithm were closer to the optimal solutions than those obtained with the Genetic Algorithm. Karaboğa and Akay [58] tested the performance of the ABC algorithm on 50 benchmark functions with different characteristics and compared the results with GA, PSO, and DE algorithms, determining that the ABC algorithm outperformed the other algorithms.

5. Conclusion and recommendations

The genetic algorithm optimization, particle swarm optimization, and artificial bee colony optimization used to determine egg freshness show that these methods are insufficient for the intended purpose. The obtained discrimination coefficients are quite low, clearly indicating that these methods cannot be used for the intended purpose. It is understood that the problem of determining egg freshness, which cannot be solved linearly, needs to be solved using artificial intelligence techniques.

The failure of genetic algorithm optimization may have been due to the instability in random selection in large datasets or the complete dependence on chance and probability of GA optimization. The failure of the particle swarm optimization algorithm may be due to the tendency to fall into local optimality easily in solving the large-scale combinational optimization problem due to the inertia that it carries about the balance between local search capability and global search ability.

It has been understood that the most suitable method for determining egg freshness is artificial neural networks. It has been determined that the ANN method can be effectively used for this purpose and has sufficient accuracy to be transferred to industrial applications.

Determining the effectiveness of other optimization methods for determining egg freshness and testing new hybrid algorithms created by combining these algorithms may be useful for future studies. The results obtained show that artificial neural network optimization is an effective algorithm that can be transferred to industrial applications. With the help of this algorithm, artificial neural network optimization, which is used in very few studies in the animal husbandry field, can be used in more studies and can produce effective solutions.

Acknowledgements
This manuscript was simple summary of PhD thesis of the first author.

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