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Use Of Deep Learning To Determine The Freshness Of Egg

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Highlights:

- Non-destuructive
- Convolutional neural networks
- Egg Freshness

Keywords:

- Egg
- Freshness
- Deep learning
- Convolutional neural networks
- Non-destuructive

ABSTRACT:

The freshness of the egg is important for both hatching and human consumption. It is quite difficult to determine the freshness of the egg without damaging it with classical methods. Deep learning is a powerful method used to classify data without processing or with much less processing. In this study, 30 eggs were photographed as experimental material for 29 days and the images obtained were used as data. It is aimed to determine how many days old the eggs are, which are foldered according to the days of the photos obtained. As a result of the study, 91.78% valuation accuracy value was obtained. Obtaining inputs without preprocessing shows that the Deep learning method can be used when a fast decision is required and the machine needs to make its own decision.

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INTRODUCTION

Eggs are a highly important, affordable, and nutritious component of human nutrition. The quality of eggs is influenced by variables such as the age of the animal, the content of feed consumed, and genotype, while storage conditions also play a significant role. As the storage duration increases, the quality of eggs tends to deteriorate. This quality encompasses both the perspective of food quality and the hatchability rate of breeding eggs (Tainika, 2023). Another critical factor contributing to egg quality is albumin (Abdel-Nour et al., 2011). Although the quality of albumin is not consistent, it varies from egg to egg. Albumin is influenced by numerous factors such as dietary content (Hossain, 2023), temperature (Karoui et al., 2006; Tabidi, 2011; Yimenu et al., 2017), relative humidity, chicken age, and storage duration (Gao et al., 2017; Dang, 2023). One of the most significant indicators of the effects of storage conditions and time on quality is the thinning of albumin. When an egg is cracked onto a smooth, flat surface, the egg yolk is typically centrally positioned, surrounded by thick albumen (Robinson & Monsey, 1972; Wells & Norris, 1987; Karoui et al., 2006). In general, machine vision systems are designed for candling and crack detection, while acoustic systems detect cracks by striking sound signals. Both technologies can also be combined in a single device, allowing for the classification of eggs based on external features and potential internal defects (Wang et al., 2010).

Various methods are employed to assess the quality of eggs, which can be categorized into two groups: methods involving the breaking of eggs and methods that do not require breaking. The Haugh unit (HU) is the most commonly used method for measuring egg quality, which is obtained by breaking the egg (Haugh, 1937). HU, reliable results for measuring egg quality, is still widely used in many studies (Dang, 2023; Narushin, 2023; Tainika, 2023). This method is based on the relationship between the weight of the intact egg and the measurement of albumen height after the egg is broken. As time passes after egg laying, both the weight of the intact egg and the viscosity of the albumen decrease due to moisture loss (Abdel-Nour et al., 2011; Dang, 2023). When eggs are broken, their freshness can be assessed. However, from an industrial and consumer perspective, determining the freshness of eggs without breaking them is economically important. Various studies have been conducted to measure the freshness of eggs without breaking them (Karoui et al., 2008; Abdel-Nour et al., 2011; Aboonajmi et al., 2014; Aboonajmi & Najafabadi, 2014; Yang et al., 2016; Shi et al., 2022; Cevik et al., 2022; Zhang et al., 2023).

Technological advancements have paved the way for the introduction of Agriculture 4.0, and as technology rapidly integrates into agriculture, developments have occurred in the field, much as expected across all sectors. The use of smart machinery, the advancement of autonomous systems, and the adaptation of robotic devices and applications in agriculture have led to improvements in areas such as productivity, rapid decision-making, water and pesticide conservation, as well as environmentally friendly solutions. In this study, an attempt was made to perform classification using deep learning convolutional neural networks, which is one of the machine learning methods.

CNN (Convolutional Neural Network) algorithm is the mathematical modeling of the visual system. The mathematical convolution process here can be thought of as the response generated by an activated neuron. CNN, which has provided some of the most successful results in the field of computer vision, is commonly used in various applications such as object recognition, segmentation, natural language processing, sentence analysis, speech analysis, biomedical applications, and prediction. Current state-of-the-art convolutional neural network architectures in the literature include LeNet, AlexNet, VGG-16, ResNet, and GoogLeNet.

The processing of all pixels in an image begins with the detection of edge features in the early layers and progresses to obtain more complex features in the deep layers. The filter is slid over the image depending on step size, and at each step, overlapping values are multiplied and the sum of all values is recorded as the respective element in the output matrix. When the filter's symmetry is not taken into account, this process is referred to as 'cross-correlation.' The filter applied to the input image is essentially a weight matrix updated through backpropagation. Before applying an activation function to the output matrix, a scalar bias (b) is added, and the result is obtained.

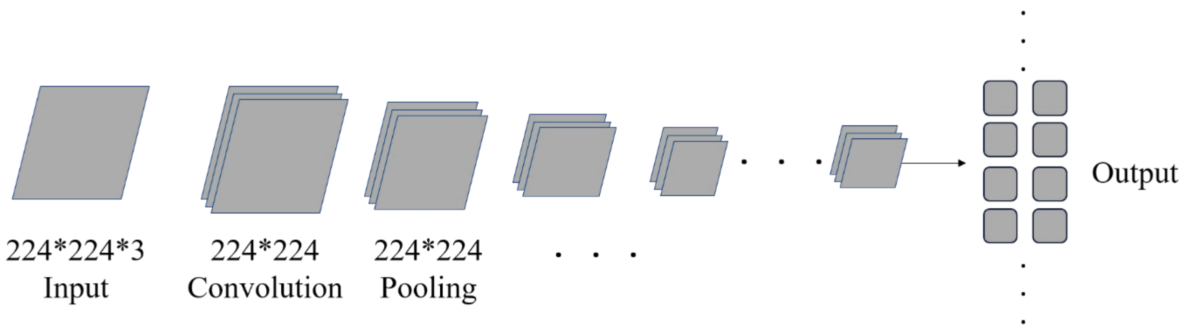

Figure 1. Convolutional Neural Network Model.

Another well-known architecture used for classification is the architecture called ResNet (He et al., 2016). The ResNet architecture is highly successful, having surpassed human-generated results in the ImageNet competition. Previously mentioned architectures like LeNet, AlexNet, GoogLeNet, and VGG are generally seen as relatively shallow structures. In such structures, as the depth of the network increases, the problem of vanishing or exploding gradients is encountered. This problem is related to the impact of the calculated error value on the network parameters during the update of the network's parameters. If the gradient value vanishes, the network parameters do not change at all, and if the gradient value goes to infinity, all network parameters go to infinity. As a result, learning does not occur in both cases. To address this problem, a shortcut connection has been added. This shortcut connection transfers the input information a few layers ahead. Thus, by ensuring that the previous layer's information is always known, the adverse effects of gradient issues are mitigated. ResNet architectures can be named according to the number of layers used, such as 18, 24, 50, 101, and 152. ResNet architectures typically start with a 7x7 pixel convolutional layer, followed by 3x3 pixel and 1x1 pixel convolutional layers depending on the depth used. The output utilizes the softmax function and can classify with 1000 different label values. It remains a widely used architecture in contemporary applications.

In this study, the aim is to determine the freshness of eggs without cracking them using deep learning methods, based on photographs taken of eggs stored in the refrigerator for 29 days.

MATERIALS AND METHODS

Material

In the experiment, white eggs obtained from a commercial farm with Leghorn laying hens were used. A total of 50 eggs laid on the same day were used as the experimental material. To transfer egg photos to the computer, a Canon 550D digital camera mounted on a tripod was used. The captured photos were saved at a resolution of 18 MP and a fixed ISO value. All optimizations and artificial neural network classification were implemented using MATLAB software.

Method

Obtaining images

The eggs were stored in the refrigerator, and they were taken out and put back into the refrigerator at the same time only when taking photos. The pointed ends of the eggs were placed facing downward in the setup. A fixed amount of light and a tripod were used with a stable camera (Figure 2).

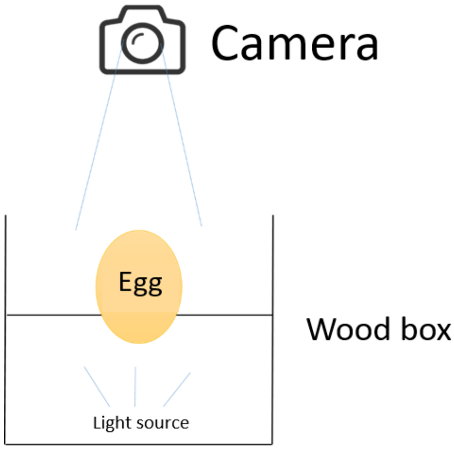

Figure 2: Photo Setup

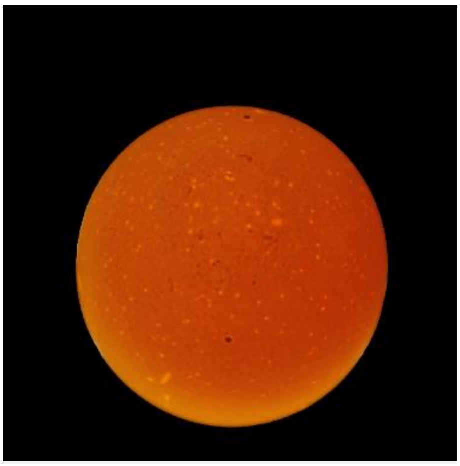

Figure 3: Object with the background removed photograph

The dirty spots in the black areas in the background of the obtained photographs were removed using image processing software (Figure 3). The obtained photographs were organized into separate folders. A total of 870 photos were collected over 29 days from 30 eggs. The U.S. Department of Agriculture determines the final sale date of eggs within 30 days after packaging (USDA, 2016), while in the EU, egg marketing regulations specify that the best before date cannot exceed 28 days after laying (EUR-Lex, 2017).

Convolutional Neural Networks (CNNs)

Deep learning can be defined as the task of training and learning from a complex artificial neural network model consisting of a large number of hidden layers. The most significant advantage of this process is the automatic extraction of features directly from raw data and the self-training of the classification algorithm based on the extracted features (LeCun et al., 2015).

Traditional classification and image processing methods cannot process raw images directly. Therefore, they require various preprocessing techniques and feature extraction algorithms. This is a challenging and experience-intensive process. Researchers have been eager to move away from manual feature extraction from the early days and desired the automatic extraction of features in the best possible way. Although this learning process has been accomplished with deep artificial neural networks, there were significant shortcomings in fields such as image processing. In this regard, research efforts have led to the emergence of Convolutional Neural Networks (CNN), which are highly suitable for the structure of images.

CNN, proposed as a deep learning architecture, is highly effective in solving image processing problems and can adapt well to images. In classical algorithms, an image is typically converted into vectors, and pixels are examined only based on specific neighborhood values, or pixels are examined independently of each other. In such cases, a lot of information about objects in the image is lost. The CNN structure eliminates this problem by using filters of the same dimensions as the image. When its architectural structure is examined, it can be seen that it contains a large number of parameters. Classical network architectures face a problem called the 'curse of dimensionality' when they contain so many parameters and are trained with massive datasets like images.

In addition, it will tend to overfit the training data and have low performance on validation and test data. To address these issues, the CNN architecture was inspired by the primate's visual cortex. The primate's visual cortex consists of various parts, and the image is transmitted between these parts. Similarly, in the CNN architecture, there are specific layers that are connected in various blocks rather than being directly connected. Information transfer between these blocks closely resembles the visual cortex, and it mitigates the problems associated with classical techniques.

Deep learning application

In this study, the ResNet architecture was utilized, consisting of 177 layers and 192 connections. The input data comprises photos with dimensions of 224x224x3. The ResNet architecture was modified, with the last convolution fully connected layer being replaced by a new fully connected layer. The input data was adjusted using 'auto input size,' and the output size data was set to '29' (representing 29 different image classes). The learning rate factors for weight and bias were adjusted by a factor of 10. 70% of the data was randomly selected for training, while the remaining 30% was reserved for validation.

RESULTS AND DISCUSSION

There is no fixed number of iterations for deep learning to achieve 100% results. The highest validation rate obtained with the use of the deep learning algorithm is recorded by the algorithm and presented as the result. The researcher can terminate the algorithm depending on the number of iterations, which varies depending on the problem. The training data achieved approximately 100% accuracy by the 180th iteration. The training data reached 100% in the 210th iteration and appeared as a straight line varying between 100-99%. In validation accuracy, it took the form of a straight line after the 210th iteration, similar to the training data. The algorithm was continued for up to 400 iterations to monitor the variability of Accuracy. Because; The study conducted 400 iterations to determine the appropriate iteration count. Cross-validation was performed every 50 iterations, and an accuracy of 91.78% was achieved at the 250th iteration.

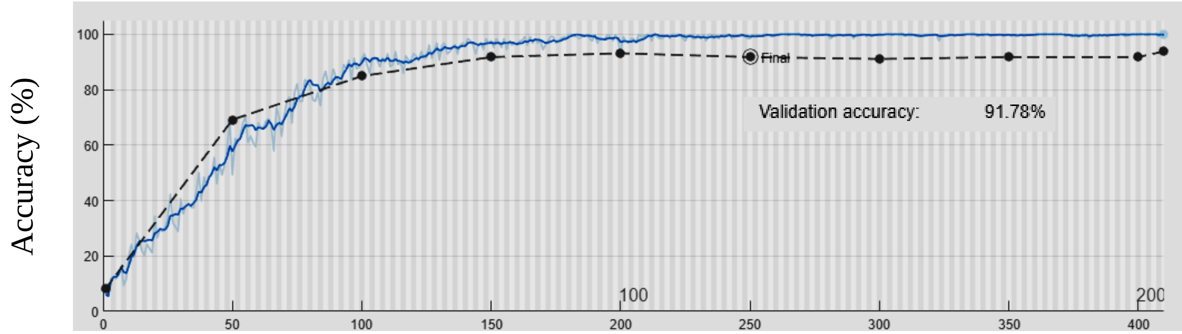

Figure 4: Iteration X Accuracy graph

This result obtained that iteration count is good enough, and validation accuracy has 91.78% high estimate value.

The results obtained from the deep learning analysis used to determine egg freshness indicate that this method is sufficient for the intended purpose. The obtained coefficient of determination is quite high, clearly demonstrating that this method can be effectively used for the intended purpose. Therefore, it has been determined that the deep learning method can be used effectively and has a sufficient level of accuracy for industrial applications.

Egg storage reduces egg weight, yolk weight, and eggshell weight linearly (Dang et al., 2023). As the storage duration increases, these changes in eggs decrease egg quality. To produce high-quality chicks, it is necessary to shorten the storage duration of fertilized eggs (Dang et al., 2023). Yimenu et al. (2017a) investigated the feasibility of using the rapid gas chromatography (GC) e-nose method to monitor egg quality and this quality during a 20-day storage period. They evaluated egg freshness using qualitative sensors and performed measurements on days 0, 3, 6, 9, 12, 16, and 20. In their study, Principal Component Analysis (PCA) and Discriminant Factor Analysis (DFA) indicated differences in volatile profiles of egg samples from seven different storage times, reporting total variances of 95.7% and 93.71%, respectively. They reported that the GC method was successful in predicting the egg freshness index with the obtained values. Unlike our study, Yimenu limited the study duration to 7 observations between days 0 and 20, which is shorter than the legal storage period (EUR-Lex, 2017; USDA, 2016). The method they applied in their studies requires cost, time, and expertise. In another study, Yimenu et al. (2017b) examined the effect of long-term storage on egg freshness and reached bias factor values ranging from 0.94 to 1.116, which were considered acceptable, for predicting freshness-affecting parameters. Dong et al. (2018a) investigated freshness indicators of eggs such as HU unit, yolk index, and albumen pH with the non-destructive method using Partial Least Squares Regression (PLSR), and were able to predict egg values with importance degrees of 0.881, 0.903, and 0.888 (p), respectively. Again, Dong et al. (2017; 2018b) measured eggshell and air cell diameter with the PLSR method and achieved accuracy values of 0.84 and 0.85 (p). Aboonajmi et al. (2016) obtained R^2 values of 0.941 and 0.898 in their study using ANN to predict HU and air cell height. These studies demonstrate the prediction of parameters required to estimate egg freshness. Predicting these values with a prediction method that works with 95% accuracy will result in a 5% higher error rate. Coronel-Reyes et al. (2018) attempted to predict egg storage time using NIR spectroscopy. The accuracy (R^2) obtained from the study was 0.873. While this study is similar to ours in predicting egg storage time, the accuracy value (0.873) obtained from their method was lower than the accuracy value we obtained (0.9178). In remote sensing studies, when the goal is to measure egg freshness parameters, remote predictions are not sufficient. The reason for this is that the egg is a biological cell and the values vary according to various genotypic characteristics. When it comes to egg freshness, it is necessary to evaluate the egg as a whole, not just freshness variables, as in our study.

In order to determine egg freshness, it may be beneficial for future studies to assess the effectiveness of different optimization methods and experiment with new hybrid algorithms created by combining these algorithms.

Thanks to deep learning, a method with limited application in the field of animal husbandry, can be utilized more extensively and has the potential to generate effective solutions. Increasing the number of studies, organizing and modifying all components from the input method, and making adjustments at different ratios are predicted to yield better results.

Deep learning enables the program to generate input values without extensive preprocessing of raw data or with minimal preprocessing, which allows the created network to make rapid decisions. This outcome demonstrates that the deep learning method is applies to autonomous systems.

CONCLUSION

In remote sensing studies, when the goal is to measure egg freshness parameters, remote predictions are not sufficient. The reason for this is that the egg is a biological cell and the values vary according to various genotypic characteristics. When it comes to egg freshness, it is necessary to evaluate the egg as a whole, not just freshness variables, as in our study.

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Conflict of Interest

The article authors declare that there is no conflict of interest between them.

Author's Contributions

The authors declare that they have contributed equally to the article.

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