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ORIGINAL ARTICLE

# Egg volume prediction using machine vision technique based on pappus theorem and artificial neural network

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**Abstract** Egg size is one of the important properties of egg that is judged by customers. Accordingly, in egg sorting and grading, the size of eggs must be considered. In this research, a new method of egg volume prediction was proposed without need to measure weight of egg. An accurate and efficient image processing algorithm was designed and implemented for computing major and minor diameters of eggs. Two methods of egg size modeling were developed. In the first method, a mathematical model was proposed based on Pappus theorem. In second method, Artificial Neural Network (ANN) technique was used to estimate egg volume. The determined egg volume by these methods was compared statistically with actual values. For mathematical modeling, the $R^2$, Mean absolute error and maximum absolute error values were obtained as 0.99, 0.59 $cm^3$ and 1.69 $cm^3$, respectively. To determine the best ANN, $R^2_{test}$ and $RMSE_{test}$ were used as selection criteria. The best ANN topology was 2-28-1 which had the $R^2_{test}$ and $RMSE_{test}$ of 0.992 and 0.66, respectively. After system calibration, the proposed models were evaluated. The results which indicated the mathematical modeling yielded more satisfying results. So this technique was selected for egg size determination.

**Keywords** Egg · Machine vision system · Volume prediction · Math modeling · Artificial Neural network modeling

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## Introduction

Poultry egg is widely produced in the world. In 2011, about 65 million tons poultry egg was produced indicated the importance of this nutrient food material (Anon 2012). This large amount of egg production needs the appropriate systems for performing of different post processing and measurements such as grading and sorting.

Appearance and size are the main key quality attributes evaluated by consumers and are critical in the acceptance of egg. So these characteristics must be considered in sorting treatment. Previous researchers demonstrated that egg weight is a sufficient attribute for predicting other shell egg properties such as hatchability. Wilson (1991) proposed that sorting eggs by weight prior to incubation, might be advantageous to improve pullet uniformity and efficiency. Based on studies carried out by Narushin (2005), egg geometrical properties (volume and surface area) have important roles in the poultry industry and in biological studies, as they can be used in research on population and ecological morphology, chick weight prediction, shell quality inspection and egg interior parameters.

In egg weight determination, Asadi and Raoufat (2010) developed a machine vision (MV) system in combination with an artificial neural network (ANN) technique. The MV system was composed of a CCD camera, a capture video, a lightning system and a mirror. From each sample two images were captured and processed. The needed features were calculated for each image and fed to a multilayer perceptron (MLP) network with different training algorithms. They obtained the correlation coefficient between estimated and measured egg weight as 0.96 with maximum absolute error of 2.3 g. Javadikia et al. (2011) predicted egg weight with image processing (IP) and ANFIS model. They measured the width and length of egg by real time IP, designed an ANFIS model and extracted the best relation between IP outputs and the weight of eggs. They obtained the R value and Mean Absolute Error (MAE) for actual and predicted weight of eggs as 0.9942 and 0.3285 g, respectively. Other studies have been conducted in egg weight prediction (Narushin 2005; Asadi et al. 2012; Rashidi and Gholami 2011). Machine vision technique has been utilized for other agricultural materials. Du and Sun (2006) developed an automatic method for ham surface area and volume estimation using IP method. Omid et al. (2010a) applied IP technique for estimating volume and mass of citrus fruits. Also the IP method has been used for watermelon volume (Koc 2007), orange volume and surface area (Khojastehnazhand et al. 2009) and saffron crocus corm mass (Hassan-Beygi et al. 2010).

Jin et al. (2011) indicated that egg weight loss is one of the parameters that are greatly influenced according to the temperature and period of storage. Egg weight loss occurs as a result of moisture and $CO_2$ losses through the shell pores. So prediction of egg weight using image processing is not appropriate operation because the accuracy of egg weighing system based on MV technique is function of storage time and temperature. But egg volume is an invariable parameter and can be used as a size index.

ANNs are widely used in food engineering. ANNs construct a suitable relationship between input data and the target responses without any need for a theoretical model with which to work (Hua et al. 2011). ANNs can be applied in almost every aspect of food processing, from raw material assessing (Wang et al. 2008a; Pan et al. 2009), thermal processing (Houessou et al. 2008; Hernandez 2009; Omid et al. 2011), fermentation (Wang et al. 2008b), enzymatic hydrolysis, antioxidant activity and anthocyanin content (Taghadomi-saberi et al. 2013), ultra-filtrating (Sun et al. 2004) and drying (Poonnoy et al. 2007; Omid et al. 2009) to composition detecting (Afkhami et al. 2009; Torrecilla et al. 2008), quality-assessing (Dutta et al. 2003; Sobel and Ballantine 2008; Pan et al. 2011) and safety-evaluating (Gupta et al. 2004; Panagou et al. 2007).

This study aims to design and develop a new method of egg volume prediction based on a MV system. For calibration of developed system, mathematical approximation and ANN technique were used. A statistical comparison was performed between these methods and the best model was selected for egg volume prediction.

## Material and methods

### Mathematical approximation

In mathematical modeling of egg, the Pappus's second centroid theorem was used (Thomas et al. 2006). The second theorem states that the volume of a solid of revolution generated by rotating a plane figure about an external axis is equal to the product of the plane area and the distance traveled by its geometric centroid based on Eq. 1 (Thomas et al. 2006).

$$V = A \times d \tag{1}$$

where $V$ is the volume of solid, $A$ is plane area and $d$ is the traveled length of plane's centroid.

In egg volume approximation, it is assumed that the volume of an egg is performed by rotation of two half planes obtained from dividing of projected area into two sections in line of longitudinal axis (Fig. 1). If each half plane rotates 180° about major diameter of egg (longitudinal axis), the whole egg will be generated.

So the volume of an egg can be obtained by following equation:

$$V = \sum_{i=1}^{2} V_i \tag{2}$$

$$V_i = \pi \times R_i \times A_i \tag{3}$$

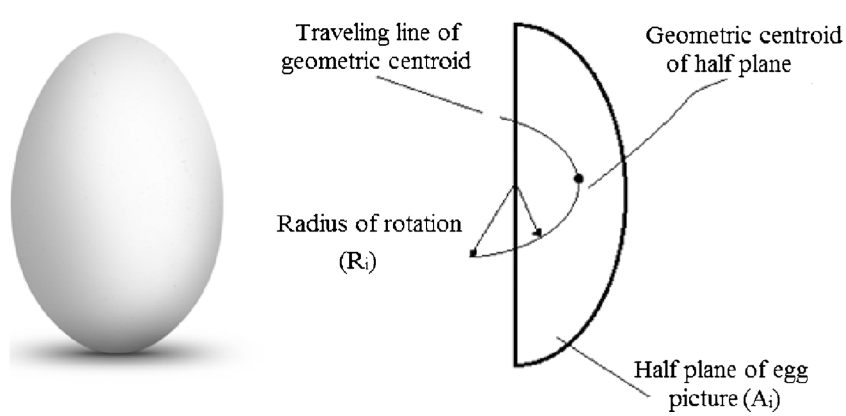


**Fig. 1** A plot of half part of egg for mathematical modeling

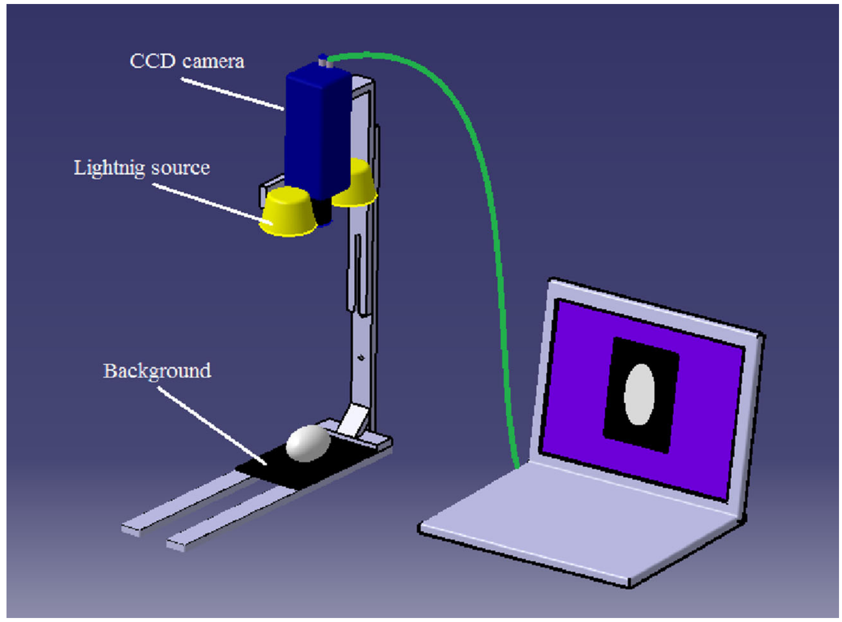


**Fig. 2** Designed machine vision system for egg mass prediction

where $V$ is the volume of whole egg, $V_i$ is the volume of solid substance generated by revolution of half plane, $R_i$ is the radius of traveling line and $A_i$ is the area of half plane

## Artificial neural network (ANN) modeling

Among ANN architectures, MLP networks are commonly used for classification and function approximation in agri-food products especially for sorting, grading and quality predictions (Omid et al. 2009; Omid et al. 2010b; Mollazade et al. 2012). The structure of MLP is composed of an input layer, one or more hidden layer (s), and an output layer.

The MLPs are usually trained by error backpropagation algorithm. Error minimization can be obtained by a number of procedures including gradient descent (GD), Levenberg-Marquardt (LM), and conjugate gradient (CG) (Omid et al. 2009; Omid et al. 2010b). Here, LM algorithm is used for error minimization, as this algorithm was designed to approach second-order training speed without having to compute the Hessian matrix (Omid et al. 2010b). The egg's major and minor diameters were selected as input parameters whereas the ANN output was the volume of egg.

The topology of ANN (number of hidden layers and neurons) has an important role in accuracy and computational burdens of networks. The complexity of the problem indicates the number of hidden layers and neurons (Mollazade et al. 2012). In this study, one hidden layer with variable neuron number (2 to 50 neurons) was used for developing the MLP network. MATLAB software, version 2012b (8.0.0.873) was used for the design and testing of ANN models (MathWorks 2012).

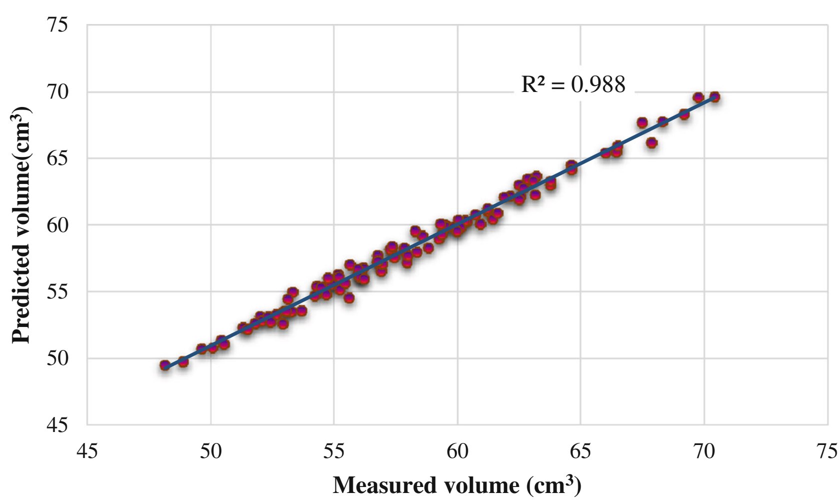


**Fig. 3** Predicted volume obtained by mathematical model vs. measured volume in calibration mode

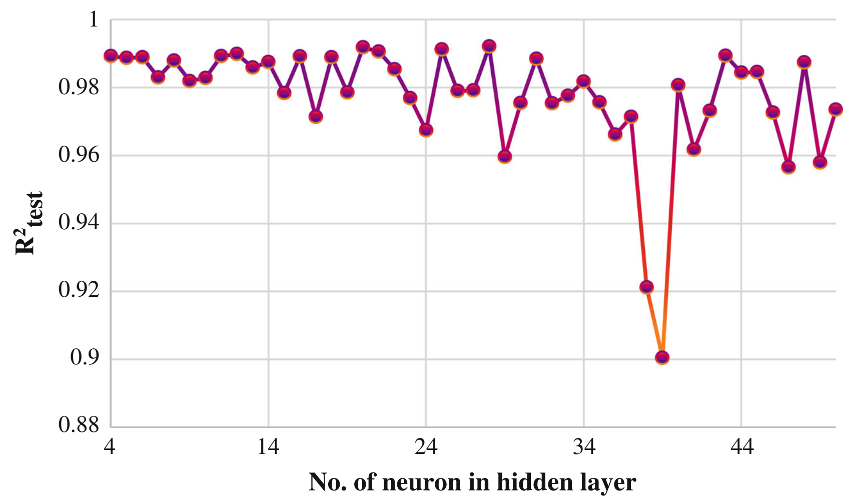


**Fig. 4** The obtained $R^2_{test}$ values for different ANNs

## Statistical analysis

To evaluate the performance of ANNs and determine the best model, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) of the difference between the experimental and calculated values and coefficient of determination ($R^2$) were used for tested models. Eq. 4, Eq. 5 and Eq. 6 represents the RMSE, MAE and $R^2$ equations, respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{n}|P_i - O_i|}{n} \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\left(P_i - \bar{O}\right)^2} \tag{6}$$

where $P_i$ is the network (predicted) output from observation $i$, $O_i$ is the experimental output from sample $i$, $\bar{O}$ is the average value of experimental output, and n is the number of samples.

## Machine vision system

To determine the volume of egg samples, a machine vision (MV) system was designed and developed. The MV system consisted of a CCD camera (PROLINE UK, Model 565 s), a USB capture card (USB 2.0 Video Capture Device, pin Avid, Germany), a lighting source with 10 super high bright LEDs (2 V, 40 mW) and a personal computer (PC). To simplify the segmentation of egg pictures from captured images easy, a black sheet was used as background. The camera was mounted about 40 cm above the background and perpendicular to it. Figure 2 shows the developed MV system. The procedure of system design consists of three subsections: image acquisition, image processing and computation of main diameters of eggs. In acquisition step, an image was captured from each sample in RGB color space and saved in MATLAB

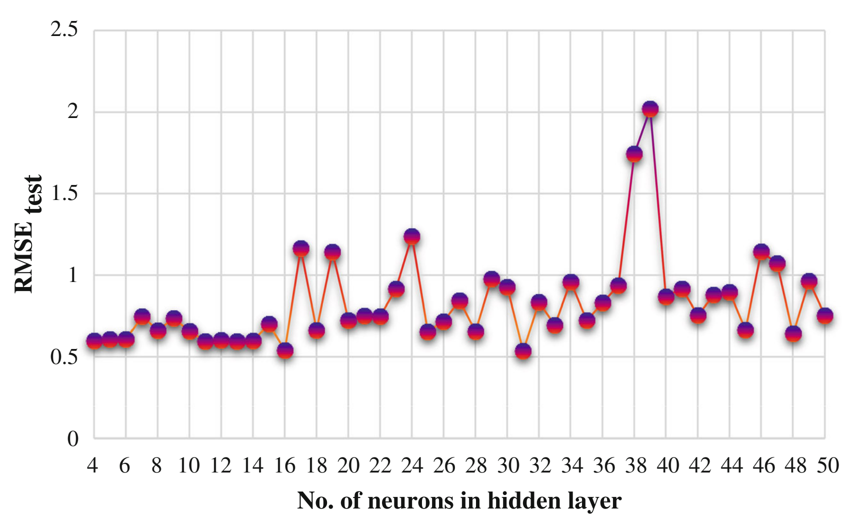


**Fig. 5** The $RMSE_{test}$ value of ANN models with different number of neurons in the hidden layer

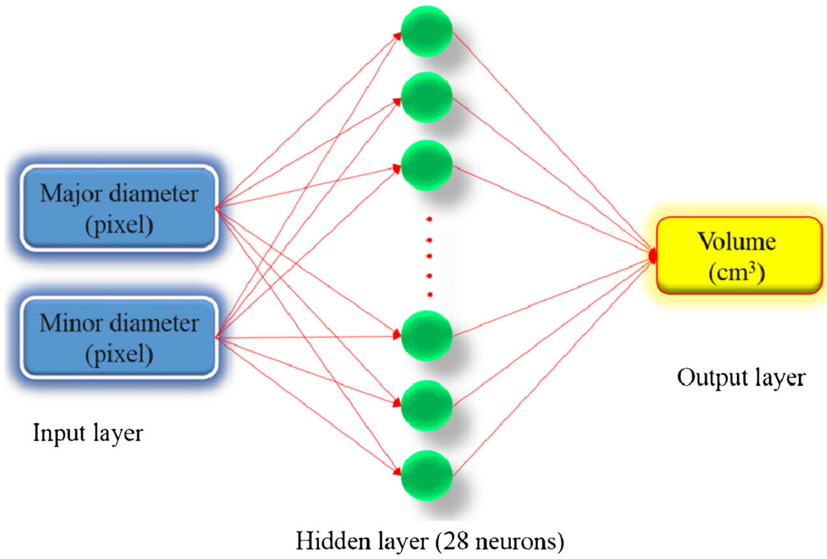


**Fig. 6** The structure of the best ANN structure for egg volume prediction

software. In image processing operation, the unwanted parts of images were cropped and the modified image was converted from RGB space to binary format.

Undesirable stains and holes in images (due to dirt, breakage and cracks) affected the pixel numbering and caused a high error in size determination. In order to eliminate these areas, the *imfill* function was used for this purpose. The algorithm of this function operates based on morphological reconstruction on binary images (Omid et al. 2013). To separate eggs from background, the segmentation was carried out on the images using automatic thresholding. In this method, the program finds the best threshold for each image separately. Finally, using the *regionprops* function, the dimensional properties of egg pictures were extracted. These properties included major and minor diameters of whole egg (in pixel unit), centroid and area of each half part. After design of MV system, experiments were carried out for its calibration and accuracy performance evaluation.

Sample preparation

The 125 intact egg samples were randomly collected on a laying day from Agricultural Community and Animal Husbandry of Iranians Modern Farms (*Varamin* unit) located in *Tehran* province and were transferred to the Instrumentation Laboratory, Department of Agricultural Machinery Engineering, Faculty of Engineering and Technology, University of Tehran, Karaj, Iran. Samples were divided into two groups: 80 % for system calibration (100 egg samples) and 20 % (25 egg samples) for evaluation purpose. The actual value of egg's main diameters and mass were measured using a digital caliper (accuracy; 0.01 mm) and a digital balance (accuracy; 0.01 g), respectively. The volume of eggs was determined using mass of samples by Eq. 7:

$$V_a = \frac{m}{\rho} \tag{7}$$

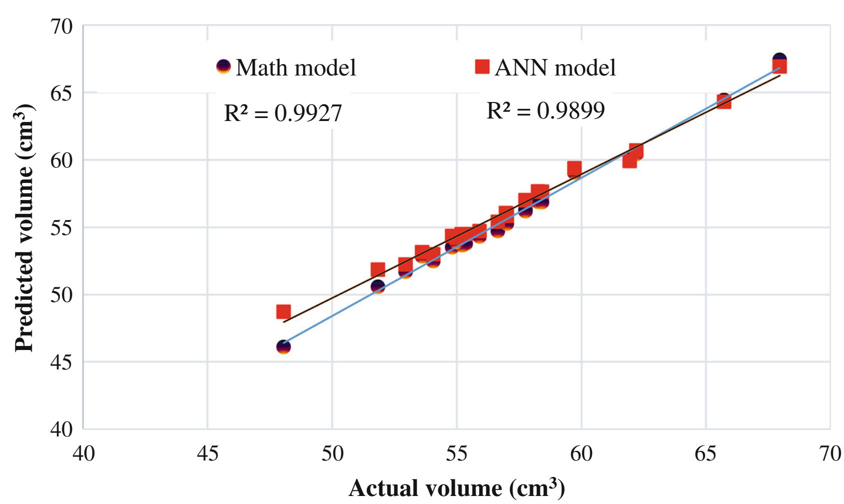


**Fig. 7** Result of machine vision evaluation

**Table 1** Result of statistical analysis of proposed models for egg volume ($cm^3$) prediction

| Method of prediction | $R^2$ | STDEV of absolute difference | Mean absolute difference | Maximum absolute difference |
|---|---|---|---|---|
| ANN modeling | 0.990 | 0.426 | 0.89 | 2.06 |
| Math modeling | 0.993 | 0.393 | 1.41 | 1.96 |

where $V_a$ is the actual volume of egg ($cm^3$), $m$ is the mass of egg (g) and $\rho$ is the density of egg ($g/cm^3$). The density of fresh egg assumed 1.035 $g/cm^3$ (Stadelman and Cotterill 1995).

## Results and discussion

The egg samples prepared for system calibration and evaluation had the mean value of 58.12 $cm^3$ for volume, 57.12 and 43.95 mm, with standard deviation of 4.5 $cm^3$, 1.95 and 1.29 mm for volume, major and minor diameters, respectively.

The predicted volume of eggs from mathematical model in calibration mode was compared with actual ones (Fig. 3). The $R^2$, MAE and maximum absolute error values were 0.99, 0.59 and 1.69 $cm^3$, respectively. The obtained results are better than results of Asadi et al. (2012). They used multiple linear regression (MLR) in egg mass prediction and obtained the best model with $R^2$ of 0.968 and maximum error of 5 g, respectively. So the proposed model is more efficient than MLR obtained by Asadi et al. (2012).

To develop the ANNs, the calibration data was divided into 3 groups: 70 % for training, 15 % for cross validation and the remaining for test purposes. To determine the best structure of ANN, the $R^2$ and RMSE values of test data were obtained. The networks with 2 and 3 neurons in the hidden layer had the lowest performance and so they were eliminated.

Results of ANN modeling with different number of neurons in the hidden layer are presented in Figs. 4 and 5. Among the designed networks, the best model with 2-28-1 topology had the highest value of $R^2_{Test}$ (Fig. 4) and an acceptable value of $RMSE_{Test}$ (Fig. 5), i.e., a network with two inputs (egg's major and minor diameters), one hidden layer (with 28 neurons), and one output (volume of egg) (shown in Fig. 6). The $R^2_{test}$ and $RMSE_{test}$, of the best network were 0.992 and 0.66 $cm^3$, respectively. The obtained results are better than results of Asadi and Raoufat (2010). They obtained the correlation coefficient and maximum absolute error as 0.922 and 2.3 g for the best algorithm.

In order to evaluate the performance of developed models, the volume of evaluation specimens was predicted using mathematical and ANN models. Figure 7 shows the predicted volume by these methods versus the actual volume. Table 1 represents the statistical results of evaluation.

## Conclusion

In this study, a simple machine vision system was developed for egg volume estimation. The mathematical and ANN models were developed and validated. Results of model validation confirmed the good performance of two methods. After calibration of system, another experiment was performed. Evaluation results demonstrated the superiority of the mathematical modeling. Both methods were quite general and may be readily applied for volume computation of other ellipsoidal agricultural products such as citrus fruits, limes, peaches, onions, melons, kiwifruits, pomegranates, pears, etc.

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