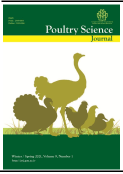

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Comparing the Accuracy of Artificial Neural Networks in Estimating the Weight of Cobb, Ross, and Arbor Acres Chicks using Video Image Processing Technology

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Abstract

This study aimed to compare the accuracy of artificial neural networks (ANNs) in estimating the weight of broilers using video image processing technology. A total number of 900 broiler chicks from three different strains (Ross 308, Cobb 500, and Arbor Acres) were fed on commercial diets and reared under standard situations for 42 days. Thirty male and female chicks from each strain were weighed randomly using digital scales every day while simultaneously filmed from top view using a Xenon camera (2MP 1080IP lens). In image processing, digital images initially were extracted from films and then each image was processed using GUI of MATLAB software. Sixteen morphological features extracted from images that significantly correlated with the chicks' weight, were used as inputs of the artificial neural network, and multilayer perceptron ANN was trained to predict the weight of chickens of each strain via an error propagation algorithm. The procedure was the same for all three strains. The accuracy of ANN models to predict the weight of chicks were 98.4% (with an average error of 7.9 g), 99.54% (with an average error of 0.37 g), and 99.67% (with an average error of 2 g) for Ross, Cobb, and Arbor Acres strains, respectively. In conclusion, a comprehensive intelligent model can be designed based on artificial neural networks and video image processing technology to estimate the weight of broiler chickens regardless of their strain type.

Introduction

Monitoring broiler weights is one of the important indices in poultry industry productivity, since factors such as low dietary nutrients may cause impressive low weights (Hashemi, 2013). Incidentally, measuring and recording the production parameters in poultry and livestock is usually time-consuming, laborious, and sometimes costly. For example, weighing the chickens requires workers to take the chickens and weigh them on scales, and this causes anxiety in the herd. Animal growth is a sequence of regular changes in the physical dimensions of an animal that follows a mathematical pattern (Buzala and Janicki, 2016). This pattern can be a basis for overcoming the birds handling issues. Image processing is a subset of machine vision that uses analog and digital image properties to identify objects and subjects, classify them, or estimate their area and weight. Our earlier study showed that image processing and data mining can help to estimate the weight of Ross broilers from their fixed images (Khojastehkey *et al*., 2015).

It is of great interest to know if the intelligent system function is the same in estimating the weight of different broiler strains. In other words, is it possible to estimate the growth rate of broiler using a comprehensive, unified intelligent model? There is a significant relationship between the volume and body weight of birds. On this basis, mathematical models can be developed and extended to estimate the weight of the bird or animal from physical dimensions such as body length, height, and width. Due to the asymmetric and irregular shape of the body in birds, it is not possible to easily estimate the upper and lateral dimensions of the body, as well as its area

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However, artificial intelligence and machine learning techniques nowadays, can ease the problem and visualize the area and environment of the bird from their digital image properties by image processing.

Machine vision technology is a subset of machine learning in computer science that is capable to analyze, detect, and decide about subjects instead of the human via image processing and data mining (Gonzalez and Wood, 2002). It is reported that the accuracy of estimation of linear, quadratic, and cubic regression models varied from 24.62 to 81.93% (Durosaro *et al*., 2013). There are numerous reports on the use of machine vision technology and image processing to estimate the qualitative and quantitative parameters in poultry. Carcass fat percentage could be estimated in broiler using machine vision technology with 0.83 to 0.86 correlations between values of carcass fat and the values estimated by Artificial Intelligence (Chmiel *et al*., 2011). The body area of broilers was estimated using digital image processing technology with 99% accuracy (Yanagi Júnior *et al*., 2011). In the meantime, egg fertility (Bhuvaneshwari and Scholar, 2015), body weight (Mollah *et al*., 2010), and broiler growth rate (Souza *et al*., 2013; Khojastehkey *et al*., 2015) were other traits measured with machine technology. It is reported that the Ross AP95 broilers showed the best growth rate and feed efficiency than the Hubbard Flex, Cobb 500, and French strains, whereas the Cobb 500 had the best breast meat yield among the studied strains (Nogueira *et al*., 2019).

It is demonstrated that the Hybro plus and Cobb 500 broilers had the best final weight at the end of the rearing period compared to the Ross 308 and Ross 508 (Fernandes *et al*., 2013). The results of these studies confirmed that usually, different strains had a different performance at the same ages. On contrary, the results of some researches showed that there were no significant differences among different broiler strains in terms of feed conversion ratio and growth rate. For example, it is revealed that the numerical differences between the weight of four strains of broiler chickens including Hubbard, Cobb 500, Ross 308, and Indian River were statistically insignificant at 42 days of age (Jawasreh *et al*., 2019). According to this information, it is necessary to know if artificial intelligence is applicable in broiler breeding. The present study was designed and performed to compare the accuracy of artificial neural networks and intelligent model in estimating the weight of Cobb, Ross, and Arbor Acres chicks.

Materials and Methods

A total number of 900 broiler chickens of three strains including Ross 308, Cobb 500, and Arbor Acres were provided and grown over 42 days under the standard conditions. The experiment was conducted at Shahid Khorakian Research Farm (Iran). In each strain, the chicks were selected equally from two sexes (male and female) and all of them were raised under the same management. The vaccination program was carried out according to the schedule provided by the local veterinary office. Water and feed were provided ad-libitum to all strains in a similar way.

Phenotypic recordings and imaging

During the breeding period, 30 chickens were randomly selected from each strain and then weighed individually in groups of 2 to 10 chicks using digital scales. The accuracy of the digital scale was 1 g (manufactured by the Mizan Company). "A 2-megapixel camcorder (XENON 1080IP) was used to capture the video of chickens. The camcorder was mounted at a constant height of 160 cm above the ground. Filming was done immediately after the chicks were weighed and the videos were directly stored on a computer hard drive.

Image processing

The images were extracted from the movies which had already been stored on a computer. At this stage, 2420 images of the Cobb strain, 2550 images of the Arbor Acres strain, and 2200 images of the Ross strain were obtained. Since not all the images were of high quality, some of them were removed, and finally, 1500, 1650, and 1648 qualified images were selected from Arbor Acres, Ross 308, and Cobb 500 images, respectively. The selected images were used for image processing. Image pre-processing was done to improve image quality using the Graphical User Interface (GUI) in MATLAB (2015) software. Primary editing such as converting color image to grayscale or binary image, removing additional shadows and pixels, contrast adjustment, removing the original image from the background, image resizing, image filtering, and image segmentation was done (Figure 1).

Extracting image features and selecting effective features

Features were extracted from images using some functions available in MATLAB's GUI environment. Two kinds of images (binary and edged images) were used to extract the relevant features from the chick's images. Accordingly, 22 different morphological features were extracted from images of chickens. Some of the most important morphological features were the mean, standard deviation, distances, eccentricity, solidity, angles, the area and perimeter, major axis length, minor axis length, and equivalent diameter. All of the features extracted from images were not required to estimate the chicken's weight, and therefore, those features showing significant Pearson correlation with the chicken's weight were selected as the effective features.

Figure 1. Converting color image (left) to binary image (right) after initial editing.

Data Mining

Data mining steps were performed using neural network fitting tools (nftool) in MATLAB software. The "feed-forward neural network", trained via the "backpropagation" algorithm, was used for chicken's weight estimation. In the training process of the artificial neural network, the characteristics extracted from the images and the weights of the chicks were used as input and output of the artificial neural network, respectively. The number of neurons in the hidden layer was determined by trial and error, and the model with the highest accuracy was selected as the final model. The criterion for selecting the best model was the higher model determination coefficient value (R2) and the lower mean standard error (MSE) of one model compared to other available models.

ANN model fitting was performed for all three broiler strains via training, validation, and test, and finally, about 10% of the total images of chickens from each strain were used for the practical test of the neural network.

Results

Image processing and features extraction of images

The correlation coefficient between each strain with extracted features from its images is shown in Table 1. Out of the 22 features presented in Table 1, 16 unique features that were more correlated with chick weight at different age groups (higher than 0.8) were selected as inputs for the training of artificial neural networks. The correlation coefficient between the characteristics extracted from the images and the weights of Ross 308, Cobb 500, and Arbor Acres were slightly different, but the change in correlation coefficients between chicken's weight and image features in all three strains followed a similar trend. Among all extracted features, solidity had the lowest correlation and NNZ had the highest correlation with broiler weight in all three strains.

Weight estimation of Ross 308, Cobb 500, and Arbor Acres strains by ANN model

In Table 2, the neural network specifications in training, validation, and testing are presented. Also in Figures 2 to 4 the neural network accuracy diagrams for estimating the weight of Ross, Cobb, and Arbor Acres chicks are shown.

As mentioned in Table 2, the accuracy of the ANN model for estimating the weight of Ross, Cobb, and Arbor Acres chicks was estimated at 0.985, 0.996, and 0.997, respectively. The accuracy of the artificial neural network model for estimating the weight of Ross chickens was about 1% lower than Cobb and Arbor Acres chicks, however, the results obtained in the present study showed that the protocol designed based on the use of video image processing and artificial neural network was successful to estimate the weight of chicks from different strains.

Table 1. Correlations between the chicken weights and the extracted features from digital images

images	features	Ross 308	Cobb 500	Arbor Acres
Binary image	Filled Area	0.97**	0.99**	0.99**
	Area	0.98**	0.99**	0.99**
	Perimeter	0.92**	0.93**	0.94**
	Major axis length	0.89**	0.92**	0.92**
	Minor axis length	0.89**	0.92**	0.93**
	Equivalent diameter	0.91**	0.91**	0.92**
	Bonding Box	0.42*	0.31	0.33
	Solidity	0.22	0.14	0.15
	NNZ	0.99**	0.99**	0.99**
	Convex Area	0.98**	0.98**	0.99**
Edged image	Bonding Box	0.44*	0.33	0.34
	Filled Area	0.86**	0.94**	0.96**
	Area	0.97**	0.94**	0.94**
	Perimeter	0.91**	0.88**	0.88**
	Major axis length	0.88**	0.91**	0.92**
	Minor axis length	0.90**	0.91**	0.92**
	Equivalent diameter	0.64*	0.71*	0.72*
	Euclidian distance	-0.69*	-0.77*	-0.73*
	Solidity	0.03	-0.11	-0.15
	NNZ	0.97**	0.94**	0.95**
	NNZ of skeleton	0.92**	0.96**	0.94**
	Convex Area	0.95**	0.98**	0.96**

** indicates the presence of a significant correlation between the chick's weight and the characteristic at 99% probability level and * 95% probability level.

Table 2. Summary of the performance statistics of the optimal ANNs for Estimation of the weight of broilers

Strain	ANN structure*	ANN accuracy			
		training	validation	test	total
Ross 308	16-14-1	0.986	0.982	0.981	0.985
Cobb 500	16-10-1	0.996	0.997	0.995	0.996
Arbor Acres	16-10-1	0.997	0.996	0.997	0.997

*Assuming the highest accuracy, the number of neurons in the hidden layer was determined by trial and error.

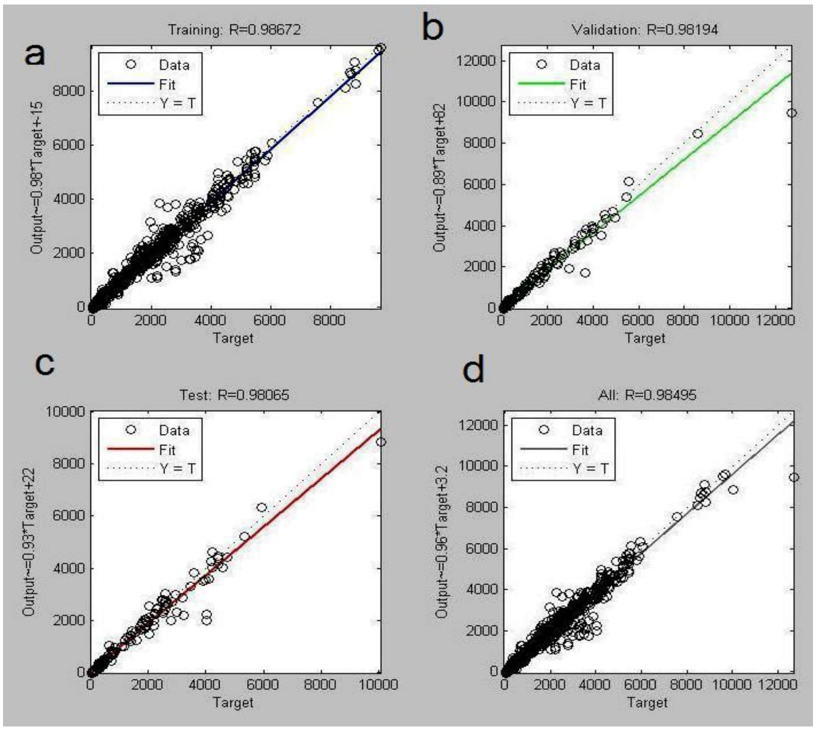

Figure 2. The accuracy diagram of ANN for estimating the weight of Ross chicks during training (a), validation (b), test (c), and overall (d).

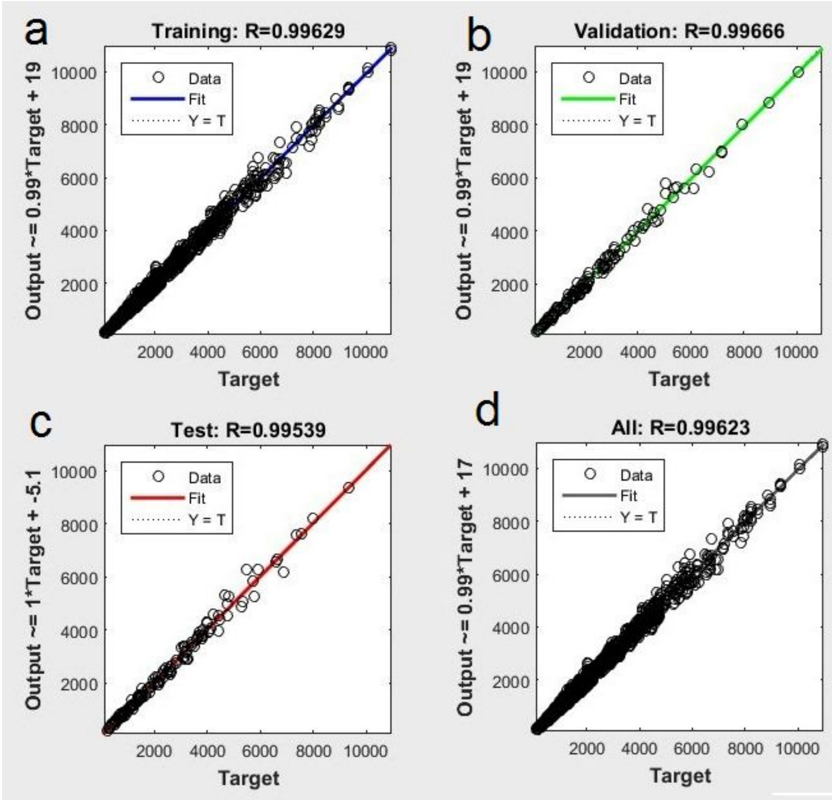

Figure 3. The accuracy diagram of ANN for estimating the weight of Cobb chicks during training (a), validation (b), test (c), and overall (d).

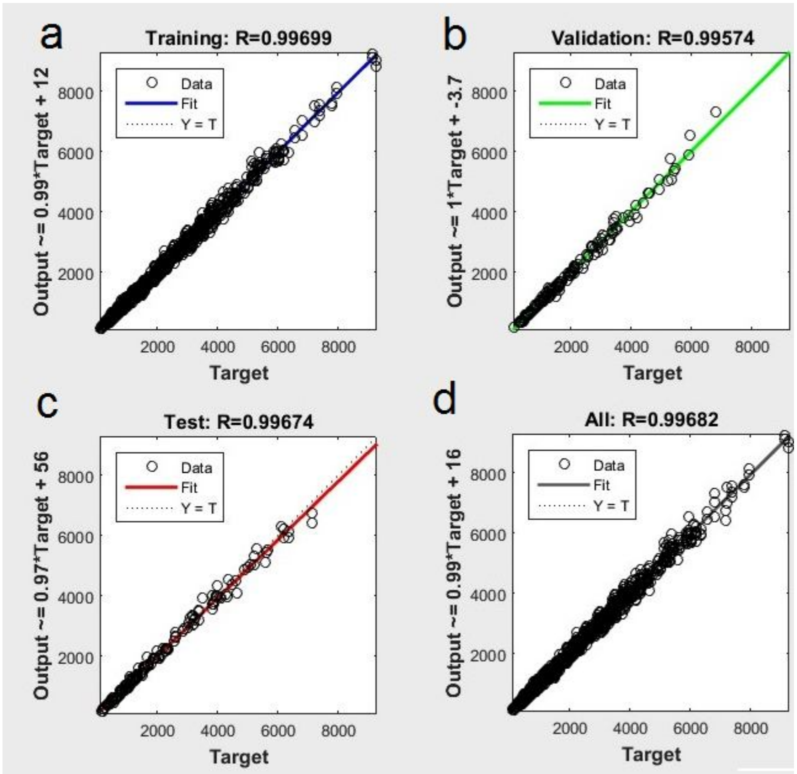

Figure 4. The accuracy diagram of ANN for estimating the weight of Arbor Acres chicks during training (a), validation (b), test (c), and overall (d).

Comparison of the prediction of ANN model with actual weights

To test the performance of the final ANN model, information on some chicks not used in the initial training steps was used in the practical test. In the practical test, the correlation coefficient between the actual weights of Ross, Cobb, and Arbor Acres chicks and the weights estimated by ANN were 99.5, 99.5, and 99.7%, respectively (Table 3). The mean deviation of actual weight from the estimated weight of Ross, Cobb, and Arbor acres chicks by the ANN model was 7.9, 0.38, and 2.00 g, respectively. According to Table 3, the maximum deviation between actual weight from estimated weight for Ross, Cobb, and Arbor Acres chicks were -66.80, -21.78, and -42.42 g respectively.

Table 3. Comparison of ANNs error in estimating the weight of broilers in a practical test

Weight categories	Arbor acres	Cobb	Ross
38 to 250 g	12.55	19.2	-39.5
251 to 500 g	31.19	19.81	-15.2
501 to 1000 g	9.82	5.62	-66.8
1001 to 1500 g	8.39	2.49	17.9
1501 to 2000 g	-42.61	17.83	13.6
2001 to 3000 g	-2.99	-21.78	47.8
More than 3000 g	1.16	-9.04	31.3
Mean of deviation	2.0002	0.38	-7.9
Correlation between actual and estimated weight	99.7	99.5	99.5
Number of the test sample	248	298	353

Discussion

Selection of effective features

The number of pixels in a digital image is directly correlated with the size and volume of objects such as people or animals. Therefore, the number of pixels in the image increases and decreases with changes in the size of objects (Souza *et al*., 2013). In contrast, the size of objects is directly related to their weight. Consequently, it can be said that the number of pixels in digital images was correlated with the weight of the objects or animals in the current study.

The morphological features of digital images were mainly changed by changing the situation, dimension, and distance of objects in the digital images. On the other hand, as the size of chickens as well as their body weight increase during the fattening period, and consequently this physiological growth is statistically correlated with increasing the chicken's body dimensions. So a positive and high correlation between morphological characteristics extracted from the images of chickens and their body weight is predictable at different ages. These positive and high correlations are the basis of the extension of the ANN model for estimating the body weight of chickens using their image morphological features (Amraei *et al*., 2017). Similar results have been reported by numerous researchers.

It is reported that there is a significant relationship between morphological characteristics such as area, perimeter, major axis length, and minor axis length with broiler weight (Amraei *et al*., 2017). Khojastehkey *et al*. (2015) used morphological features including area, perimeter, major axis length, minor axis length, and Euclidean distance to estimate the pelt area of newborn lambs. All these reports confirm the accuracy of the present study regarding the high correlation of morphological features extracted from digital images with chick weight in different strains.

Data mining studies

The proposed method based on image processing and artificial neural network perfectly estimated the weight of Cobb, Ross, and Arbor Acres chicks from their digital image features (accuracy of 98.5 to 99.7%). The accuracy of the ANN model in our study was similar to other reports in this field, and even in some cases is better than others. For instance, using the image processing technology, the live weight of buffaloes from their lateral area with 90% accuracy (Negretti *et al*., 2007), and the broiler growth rate with 90% accuracy (De Wet *et al*., 2003) were reported.

At the same time, it is demonstrated that broiler chickens' weight at different ages with the accuracy of 85 to 99% could be predicted from their digital images (Mollah *et al*., 2010). In other studies, (Souza *et al*., 2013; Amraei *et al*., 2017) the weight of broiler chickens was estimated using image processing and linear regression with 96 and 94.5% accuracy, respectively. However, in the current study, the accuracy of the ANN models in estimating the broiler's weight was higher or equal to similar studies.

In the present study, the accuracy of the ANN model for estimating the weight of three different strains of Ross, Cobb, and Arbor Acres was less than 1%, and the deviation between the actual and estimated weight of the chicks also varied from 0.37 to -7.8 g in the three studied strains. Considering the real weights (1800 to 2100 g), this deviation is very low and the network performance about estimating the actual weight is acceptable.

The reason for the difference between ANN models could be due to factors such as image quality, accuracy of records, number of records, and initial image processing method (Arivazhagan *et al*., 2013). Detecting fertilized and non-fertilized eggs using two different classification methods, machine, and ANN, is reported with an accuracy of 91 and 83%, respectively (Bhuvaneshwari and Scholar, 2015). It is stated that the egg yolk status information could improve the accuracy of the model to detect the freshness of the eggs from 92 to 94%. In the present study, considering that the image quality, imaging distance, image processing steps, and even training of ANN model were the same for all studied strains, consequently the amount of information about differences in growth rate, a growing pattern of feathers, and morphological characteristics of Ross, Cobb, and Arbor Acres chicks have caused slight differences in the accuracy of the ANN model.

Based on the results of several studies, the growth pattern and growth rate of different strains of broilers differ. For example, Hybro plus and Cobb 500 broilers had the highest weight gain compared to Ross 308, Ross 508, and Cobb strains (Fernandes *et al*., 2013). Therefore, it can be concluded that the differences in the pattern of weight gain and growth rate of feathers in different chick strains may ultimately affect the body size and body dimensions during the breeding period, and these differences, consequently, have affected the accuracy of ANN models for estimating the weights of Ross, Cobb, and Arbor Acres strains.

Conclusion

The results of this study indicated that although the accuracy of the ANN model for estimating the weight of Ross 308 chicks was lower than that of the Cobb 500, and Arbor Acres strains, but the differences among the model's inaccuracy was less than 1%. Therefore, a comprehensive intelligent model using an artificial neural network and video image processing could be generalized to estimate the weights of chickens regardless of their strains, accurately.

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