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Color Computer Vision and Artificial Neural Networks for the Detection of Defects in Poultry Eggs*

V. C. PATEL, R. W. MCCLENDON and J. W. GOODRUM
Department of Biological and Agricultural Engineering and Artificial Intelligence Center, University of Georgia, Athens, Georgia, 30602-4435, USA (E-mail: rwmc@bae.uga.edu)

Abstract. A blood spot detection neural network was trained, tested, and evaluated entirely on eggs with blood spots and grade A eggs. The neural network could accurately distinguish between grade A eggs and blood spot eggs. However, when eggs with other defects were included in the sample, the accuracy of the neural network was reduced. The accuracy was also reduced when evaluating eggs from other poultry houses. To minimize these sensitivities, eggs with cracks and dirt stains were included in the training data as examples of eggs without blood spots. The training data also combined eggs from different sources. Similar inaccuracies were observed in neural networks for crack detection and dirt stain detection. New neural networks were developed for these defects using the method applied for the blood spot neural network development.

The neural network model for blood spot detection had an average accuracy of 92.8%. The neural network model for dirt stained eggs had an average accuracy of 85.0%. The average accuracy of the crack detection neural network was 87.8%. These accuracy levels were sufficient to produce graded samples that would exceed the USDA requirements.

Key words: color computer vision, neural networks, machine vision, egg grading, blood spots, dirt stains, cracks

Introduction

In modern egg processing plants, the inspection of eggs for defects (or grading) is a major bottleneck because it is largely done by human workers. Automated detection of cracked eggs is performed in a very limited number of plants, but currently no practical system for detecting blood spots and dirt stains exists. In order to obtain maximum throughput, processing speeds of over 85,000 eggs per hour are common. The demanding requirements placed on the human workers result in two types of grading errors. Overpull occurs when grade A eggs are graded as defective and underpull is when defective eggs are allowed to be included as grade A eggs. The egg producer

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must minimize overpull and underpull to maximize profits and meet USDA requirements designed to maintain the quality of the product. An automated system capable of detecting eggs with blood spots, dirt stains, and cracks would be desirable since it could reduce the work load on human graders, increase the profitability of the egg producer, and improve the quality control process.

Blood spots are internal egg defects due to hemorrhaging in the ovaries during ovulation, salmonella infection, genetics, and seasonal factors [1]. North and Bell [2] attributed blood spots also to factors such as feed and the age of the hens. The albumen in fresh eggs is frequently cloudy, making the detection of blood spots more difficult [3]. North and Bell [2] estimated the average frequency of blood spots to be 0.9%. Eggs with small blood spots less than 0.32 cm (0.13 in.) in diameter (aggregate) must be classified as grade B [4]. Eggs with larger blood spots must be classified as “loss” and be discarded. Frequently such eggs are used by the animal feed industry.

Moisture and dirt accumulation on cage floors are a cause of dirt stained eggs [2]. Egg stains may also be attributed to bleeding during egg laying and fecal matter. Little research has been done on the incidence of dirt stained eggs. In modern egg processing facilities, eggs are washed prior to grading. However, some stains may remain. Stains may also occur after washing due to the presence of other severely cracked eggs on the processing line. USDA regulations require that eggs be classified as dirty if they have moderate stains, localized stains covering not more than 1/32 of the shell surface area, or scattered stains covering not more than 1/16 of the shell surface area [4]. Bourely et al. [5] estimated a dirt-stain frequency of 1%.

North and Bell [2] estimated that between 3% and 5% of eggs are cracked before processing. Factors such as genetics, age of the hen, amount of handling during processing, environmental temperature, diseases, and humidity influence the frequency of cracks [2]. Crack frequency can range as high as 10% in cases where the flock is aged or with collection equipment problems (Dr. Danis Cunningham, August 3, 1995. Personal Communication. Professor, Poultry Science, University of Georgia, Athens, GA).

According to the USDA egg grading manual [4], a sample of grade A eggs, after grading at the processing plant, must consist of at least 87% A quality or better eggs. Of the 13% that may be of a lower quality, 5% may be checks (cracks), 1% may be grade B due to air cells, blood spots less than 0.32 cm (0.13 in.) diameter (aggregate), or other yolk defects, and 0.5% may be leakers, dirties, or loss eggs in any combination. Leakers, dirties, or loss eggs may not constitute more than 0.3% individually.

Freeman [6] discussed machine vision systems for inspection. The discussion included sensors, illuminators, and processing systems. D’Agostino [7] developed a custom machine vision system for the inspection of food. Applications of the system included determining the size and grade of citrus, and the inspection of processed meat for defects such as discoloration. Anand et al. [8] investigated the costs of a machine vision system station for grading produce. Lighting methods, cameras, and frame grabbers were discussed and their costs evaluated. The paper included a discussion on the issues that must be considered for a color-based machine vision system. Heinemann et al. [9] used machine vision to grade mushrooms based on color, shape, stem cut, and opening of the cap veil. The system was 80% accurate on average. Scanlon et al. [10] developed a computer vision system to quantify the color of potato chips. They used mean grey-scales of images to successfully detect differences in the color of potato chips.

Gittins and Overfield [11] studied alternative methods for grading eggs and developed an electronic system for measuring various characteristics of an egg such as weight, color, albumen quality, yolk color, and shell density. Elster and Goodrum [12] developed a program to analyze grey-scale images of stationery eggs for cracks. The egg was isolated from background noise and enhanced using image processing algorithms. A 96% success rate was achieved. However, the average time required to process one egg was 25.3 seconds. Goodrum and Elster [13] extended their work to detect cracks at any point on the surface of rotating eggs. The identification of cracks was dependent on the egg size and required software calibration constants.

Bullock et al. [14] provided a brief tutorial on artificial neural networks and discussed two applications – inspection of cookies for damage, and inspection of apples for bruises. The use of artificial neural networks in agriculture was discussed by Davidson and Lee [15]. Various application areas and potential uses such as planning, harvesting, sorting and inspection, image analysis, and the control of processing plants, were outlined. Timmermans and Hulzebosch [16] developed a color computer vision system for on-line inspection of flowers and ornamentals. The system used both statistical and neural networks for the classification of the plants. An on-line learning feature was also implemented. Alchanatis and Searcy [17] implemented a system for the inspection of carrots for shape and surface defects. The system used neural networks to classify carrots into two classes. Using a pipelined image processing system, grading speeds of 2 carrots per second were achieved with an accuracy of over 90%.

Patel et al. [18] used image acquisition routines from the work of Elster and Goodrum [12] to capture grey-scale images of cracked and grade A eggs. Histograms of the images were generated and used to train a neural network for the detection of cracked eggs. The model was 90% accurate and provided significant improvement in speed over the method of Elster and Goodrum

[12]. The work was extended to the detection of blood spots and dirt stains [19]. The neural network model for blood spot detection was 85.6% accurate. An accuracy of 80% was achieved on dirt stain detection.

Goal and Objectives

The overall goal of this research was to develop a coupled color computer vision and neural network system for detection of eggs with defects. The objectives of this research project were as follows:

1) to develop neural network models capable of differentiating eggs with a particular defect from eggs without that defect,
2) to develop robust neural network models with minimized sensitivity to eggs from different sources, and
3) to evaluate the computer vision and neural network system by comparing its accuracy to USDA requirements for egg processing plants and to the accuracy previously obtained with grey-scale images.

Materials and Methods

A color video camera and a color image acquisition board (frame grabber) were used to obtain color images. A Speed King^{TM} 25 W incandescent candling lamp was used to back-illuminate the egg. The lamp generated a light with an intensity of approximately 11000 lx. The image sensor was a Sony^{TM} 3-chip CCD video camera (model DXC-930) with a horizontal resolution of 0.125 mm/pixel, and a vertical resolution of 0.110 mm/pixel. The camera was equipped with a Canon^{TM} (YH17$\times$7KTS) automatic iris lens with a focal length of 55 mm. A close-up lens (Canon^{TM} model 82CL-UP800H) with a focal length of 800 mm was used to reduce the required lens-to-object distance. The distance between the lens system and the egg (object distance) was approximately 555 mm. The camera was connected to a Data Translation^{TM} DT2871 RGB/HSI color frame grabber that was used to capture the images. The board was capable of real-time capture and display of images at 30 frames per second in 16,581,375 colors. The color frame grabber had a horizontal resolution of 512 pixels and a vertical resolution of 480 pixels. The color frame grabber was installed in a 50 MHz 80486 IBM^{TM} PC compatible computer. A Sony^{TM} (model PVM-1340) color video monitor was used to observe the images of the eggs. Figure 1 shows a schematic of the imaging system.

The imaging system was used to obtain color images of defective eggs and grade A eggs. Histograms for the red, green, and blue colors were generated

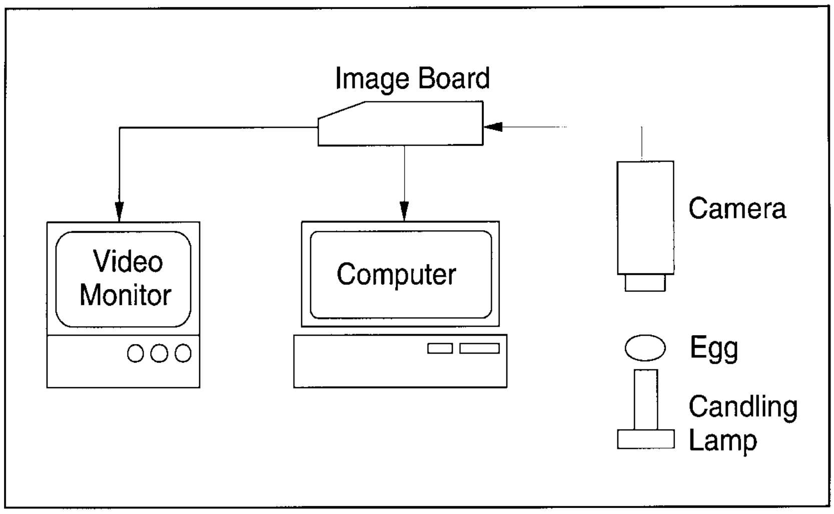

Figure 1. A schematic diagram of the imaging system.

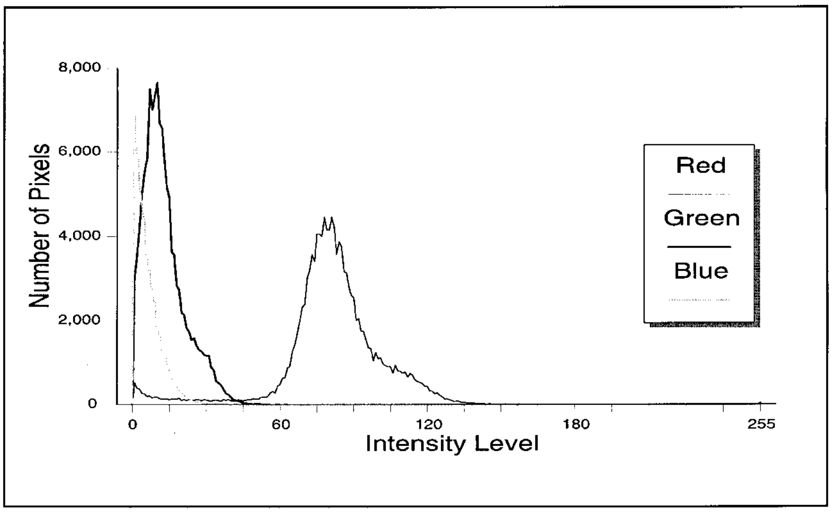

Figure 2. RGB histograms of a typical grade A egg.

from the images by counting the number of pixels at each intensity level. Since there were 256 intensity levels, this generated three histograms with 256 cells each. Figure 2 shows typical red, green, and blue histograms (with 256 cells) of a grade A egg. Although these typical histograms showed no apparent pixel counts in the region 180–255, other histograms had pixel

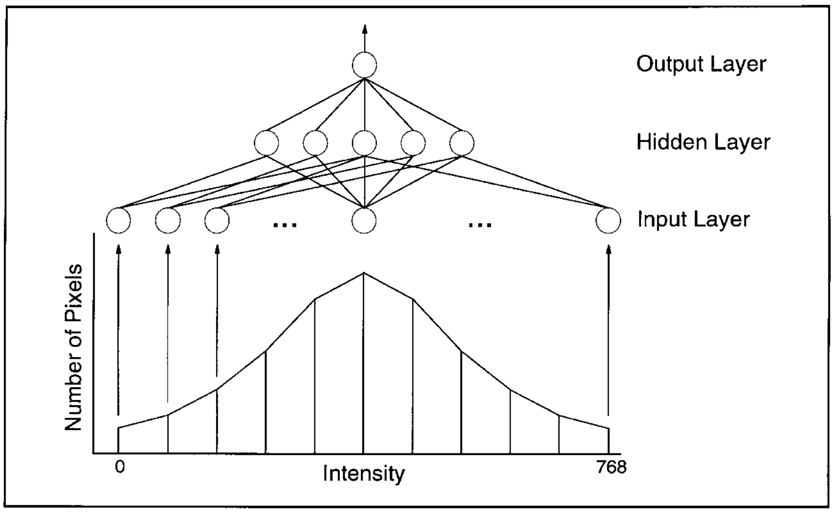

Figure 3. Histogram inputs to a neural network.

counts in this range. There were also no apparent patterns in the histograms of defective eggs which could be used to limit the range of the histogram cells. The three histograms were then joined to form a composite histogram with 768 cells and the number of pixels in the cells were used as inputs to a neural network (Figure 3). A commercial neural network simulator from Ward Systems Group, NeuroShell^{TM} 2 [20], was used in the training and testing of the neural network models. NeuroShell^{TM} 2 determines an optimal network by evaluating the predictive capability of the current neural network on an independent testing set. If the average error of the current neural network during training is less than the average error of the previous optimal neural network, the weights of the current neural network are saved as the new optimal neural network. The optimal network feature aids the user in determining when to stop training and thus develop a neural network with the maximum generalization ability. The current neural network is also saved at the end of the training session.

Professionally graded samples of 180 blood spot eggs and 180 USDA grade A eggs were obtained. The sample of blood spot eggs was exclusive to this defect. Color images of all eggs were obtained. Histograms of the red, green, and blue colors were generated from the egg images, concatenated into composite histograms, and transformed into neural network input patterns. A training set of 180 patterns was constructed by randomly selecting from the set of patterns of the blood spot eggs and the grade A eggs. From the remaining 180 patterns, another 90 patterns were randomly selected to comprise the testing set. The rest of the patterns (90) formed the validating set. The training, testing, and validating sets were constrained to have equal numbers of blood spot egg patterns and grade A egg patterns. Training, testing, and validating data for dirt stained eggs were similarly generated.

Preferred values of the neural network parameters (learning rate and momentum) were determined. Learning rate and momentum parameter values of 0.1, 0.6, and 0.9 were considered. The initial neural network structure was 768 inputs, 56 hidden nodes, and 1 output. The number of hidden nodes was varied to determine a suitable number for generalization. The values considered were 8, 24, 40, 56, 72, and 104 hidden nodes. For these models, the neural network parameter values obtained previously were used. The number of inputs was reduced to 384 by combining two adjacent cells in each histogram, and the number of hidden nodes was varied again to determine an effective neural network structure. A neural network with fewer inputs and hidden nodes is desired because it would require less computer resources. Training was stopped when either the average error on the training set was less than a preset value, or 100,000 learning events had elapsed since an optimal network was last determined, or the total number of learning events exceeded 500,000. A similar procedure was used in training and evaluating the neural network models for dirt stain detection and crack detection.

Results and Discussion[1]

The accuracy of the neural network models for blood spot detection, dirt stain detection, and crack detection was determined by applying their respective training, testing, and validating data sets to the neural network models after training was complete. Table 1 shows the accuracy of the neural networks as well as their structure in terms of the number of inputs, hidden nodes, and outputs. The blood spot detection neural network had an accuracy of 91.1% using 384 inputs and 24 hidden nodes. The highest accuracy achieved by the dirt stain detection neural network was 97.8% using 384 inputs and 40 hidden nodes. The most accurate crack detection neural network from a previous study [21] had an accuracy of 96.7%. That neural network had 384 inputs and 24 hidden nodes.

Analysis of accuracy

The USDA requires no more than 1% of grade A eggs be of B quality due to air cells, blood spots, or yolk defects. If we assume that there is an equal proportion of these defects then the final graded sample can have no more than 0.33% blood spotted eggs and no more than 0.33% dirt stained eggs. The

Table 1. Results of neural networks for detection of dirt stained and cracked eggs

Neural network	Egg defect	Network structure[1]	Learning events	Classification accuracy[2]		
				Training set	Testing set	Validating set
1.1	Blood spots	384-24-1	14300	99.4 (0/1)	93.3 (3/3)	91.1 (3/5)
1.2	Dirt stains	384-40-1	11640	100 (0/0)	96.7 (1/2)	97.8 (2/0)
1.3	Cracks	384-24-1	28480	100 (0/0)	97.8 (1/1)	96.7 (2/1)

[1] Number of inputs-Number of hidden nodes-Number of outputs
[2] % Correct (no. overpull/no. underpull)

final graded sample should also have less than 5% cracked eggs [4]. Taking a sample of 10,000 eggs of which 0.9% have blood spots, 1% are dirt stained, and 5% are cracked, which are average defect frequencies, there would be 90 eggs with blood spots, 100 dirt stained eggs, and 491 cracked eggs. The neural network model for detection of blood spots in eggs (Model 1.1[2]) was 89.9% accurate and so would pull 80 of the 90 blood spotted eggs. The neural network model for dirt stain detection (Model 1.2) had an accuracy of 100% on dirt stains and would therefore pull all 100 dirt stained eggs.

Since the crack detection model (Model 1.3) had 97.8% accuracy on cracked eggs, it would correctly identify 481 of the 491 eggs with cracks in the sample. A sample of 10,000 eggs would consist of 9,319 grade A eggs (10,000-90-100-491). The blood spot detection neural network model was 93.3% accurate on grade A eggs and so would pull 6.7% of the grade A eggs in the sample (overpull). Similarly, the neural network models for dirt stained eggs and cracked eggs both would have an overpull of 4.4%. Therefore, 1,374 grade A eggs would be pulled as overpull. The percentage of eggs with blood spots in the final graded sample would be 0.126% which is within the USDA requirement of 0.33%. Since the neural network model for dirt stain detection was 100% accurate on dirt stained eggs, there would be no dirt stained eggs in the final graded sample. The percentage of cracked eggs in the sample would be 0.126%.

Interactions of neural network models

In an actual implementation, the blood spot detection neural network would be required to inspect all eggs (i.e. blood spotted, cracked, dirt stained, and grade A eggs) when checking for blood spots. To test the accuracy of the blood spot detection neural network on other defects, it was evaluated on the training, testing, and validating data used in developing the dirt stain detection (Model 1.2) and crack detection (Model 1.3) neural networks. The blood spot neural network (Model 1.1) was chosen for this study. Similarly, the dirt stain detection neural network (Model 1.2) was evaluated on the training,

Table 2. Accuracy of neural networks trained to distinguish between eggs with a specific defect and grade A eggs, evaluated on eggs with other defects

Neural network	Egg eefect	Data set	Classification accuracy[1]	
			Grade A eggs	Defect[2] eggs
2.1	Blood spot	Crack	82.2 (32)	71.7 (51)
		Dirt stain	84.4 (28)	25.0 (135)
2.2	Crack	Blood spot	97.2 (5)	22.8 (139)
		Dirt stain	98.9 (2)	82.8 (31)
2.3	Dirt stain	Blood spot	65.6 (62)	61.7 (69)
		Crack	96.7 (6)	95.6 (8)

[1] % Correct (no. incorrect)
[2] Defect type of data set

testing, and validating data used for the blood spot and crack detection neural networks. The crack detection neural network (Model 1.3) was evaluated on the training, testing, and validating data used for the blood spot and dirt stain detection neural networks. The results are shown in Table 2.

All the neural networks had a high accuracy on grade A eggs. However, the neural networks had varying degrees of accuracy when grading eggs with other defects. The results suggest that the neural networks may be differentiating between grade A and defective eggs but not differentiating between particular defects. For a neural network to be able to differentiate between defects, it must be presented with patterns which have the specific defect and patterns with other defects during the training phase. This was accomplished by including examples of eggs with other defects in the training, testing, and validating sets.

A neural network model for blood spot detection was developed with training, testing, and validating data consisting of eggs with blood spots as examples of defective eggs, and grade A eggs, cracked eggs, and dirt stained eggs as examples of eggs without blood spots. Neural network models for crack detection and dirt stain detection were also developed in this manner. The model development method discussed above was used to obtain the most accurate neural network models. Table 3 shows the accuracy of these neural networks on the training, testing, and validating data. The neural networks were evaluated on a new batch of grade A, blood spot, cracked, and dirt stained eggs with 200 samples of each. As shown in Table 4, the blood spot detection neural network could accurately distinguish between eggs with blood spots and eggs without blood spots. The high accuracy of the blood spot detection neural network supports the hypothesis of including eggs with other defects in the training data. The crack detection neural network had a

Table 3. Results of neural networks trained to distinguish between eggs with a specific defect eggs without that defect

Neural network	Egg defect	Learning events	Classification accuracy[1]		
			Training set	Testing set	Validating set
3.1	Blood spots	37000	99.4 (0/1)	84.4 (6/8)	90.0 (3/6)
3.2	Dirt stains	11560	93.9 (0/11)	96.7 (1/2)	95.6 (0/4)
3.3	Cracks	21860	98.3 (0/3)	90.0 (3/6)	88.9 (5/5)

[1] % Correct (no. overpull/no. underpull)

Table 4. Accuracy of neural networks trained to distinguish between eggs with a specific defect and eggs without that defect

Neural network	Egg defect	Classification accuracy[1]			
		Grade A eggs	Blood spot eggs	Cracked eggs	Dirt stained eggs
4.1	Blood spots	94.5 (11)	92.0 (16)	84.0 (32)	79.0 (42)
4.2	Cracks	82.0 (36)	98.5 (3)	63.0 (74)	63.5 (73)
4.3	Dirt stains	61.5 (77)	98.5 (3)	62.0 (76)	57.5 (85)

[1] % Correct (no. incorrect)

high accuracy on grade A eggs and blood spot eggs. However, its accuracy was reduced on cracked eggs and dirt stained eggs. The dirt stain detection neural network had a high accuracy on the blood spots eggs but not on grade A eggs and eggs with other defects. In this case, the neural networks had been trained on eggs from one poultry house and tested on eggs from another poultry house. To minimize the sensitivity of the neural networks to different defects and different eggs sources, the training, testing, and validating data were expanded to include eggs from different poultry houses.

Professionally graded samples of blood spot eggs, cracked eggs, dirt stained eggs, and USDA grade A eggs were obtained. All samples were constrained to have eggs with a single type of defect or of grade A quality. Color images of all eggs were obtained. Histograms of the red, green, and blue colors were generated from the egg images, concatenated into composite histograms, and transformed into neural network input patterns. A training set of 360 patterns was constructed by randomly selecting 180 patterns from the set of patterns of blood spot eggs, and 60 eggs from each of the cracked, dirt stained, and grade A eggs. A non-overlapping testing set of 180 patterns was constructed by combining 90 randomly selected patterns of blood spot eggs, with 90 randomly selected patterns of each of the cracked, dirt stained, and grade A eggs (30 from each category). A validating set of 180 patterns was similarly

Table 5. Results of training neural networks on combinations of a specific defect and other defects from two poultry houses

Neural network	Egg defect	Learning events	Classification accuracy[1]		
			Training set	Testing set	Validating set
5.1	Blood spots	90740	99.4 (0/2)	92.2 (5/9)	92.8 (4/9)
5.2	Cracks	34960	94.7 (10/9)	86.7 (12/12)	87.8 (8/14)
5.3	Dirt stains	60440	98.1 (7/0)	85.0 (17/10)	85.0 (14/13)

[1] % Correct (no. overpull/no. underpull)

Table 6. Accuracy of neural network models on specific types of defects

Neural network	Egg defect	Classification accuracy[1]			
		Grade A	Blood spots	Cracks	Dirt stains
6.1	Blood spot	93.3	90.0	93.3	100.0
6.2	Crack	93.3	90.0	84.4	90.0
6.3	Dirt stain	86.7	90.0	76.7	85.6

[1] % Correct

constructed. The training, testing, and validating data sets were constrained to include equal numbers of eggs from two different poultry houses. Training, testing, and validating data sets for developing crack detection and dirt stain detection neural networks were similarly generated.

A new set of neural networks for blood spot detection, crack detection, and dirt stain detection were trained. As before, experiments with the neural network learning parameters and structure were performed to obtain the most accurate neural network models as shown in Table 5. The average accuracy of the blood spot detection neural network on the validation set was 92.8%. The dirt stain detection and crack detection neural networks had average accuracies of 85.0% and 87.8%, respectively.

Table 6 shows the accuracy of the neural networks on grade A eggs and various defects in the validating set. The results indicate that the neural networks trained with all defects present and with eggs from various sources were more robust when grading eggs with other defects. The average accuracy of the neural networks was less than the accuracy obtained when the data were restricted to a single defect and grade A eggs. However, the models developed for these more realistic conditions were sufficiently accurate to generate graded samples that would exceed USDA requirements. Using a sample of 10,000 eggs, the percentage of blood spot eggs in the final graded sample was 0.113%. The percentage of dirt stained eggs and cracked eggs was 0.183% and 0.774%, respectively.

Using histograms of grey-scale images to train neural networks for detection of blood spots, dirt stains, and cracks resulted in accuracies of 85.6%, 80.0%, and 90.0%, respectively [18, 19]. The neural networks trained on histograms of color images had accuracies of 92.8%, 85.0%, and 87.8% for blood spots, dirt stains, and cracks, respectively. Although the color crack detection neural network was slightly less accurate than the grey-scale crack detection neural network, the color crack detection neural network was more robust in terms of inspecting eggs with other defects. Overall, the use of color computer vision improved the accuracy of the neural networks.

Conclusions

Neural networks trained entirely on eggs of one type of defect and grade A eggs could produce graded samples that would exceed USDA requirements. However, the neural networks were less accurate for different types of egg defects and also to eggs from different sources. To minimize these sensitivities, the training, testing, and validating data were modified to include examples of eggs with other defects and eggs from different poultry houses. The resulting neural networks were more robust and able to differentiate between the different types of defects.

The neural network model for blood spot detection had an average accuracy of 92.8% (90.0% on blood spot eggs and 95.6% on eggs without blood spots). The neural network model for dirt stained eggs had an average accuracy of 85.0% (85.6% on eggs with dirt stains and 84.4% on eggs without dirt stains). The average accuracy of the crack detection neural network was 87.8% (84.4% on eggs with cracks and 91.1% on eggs without cracks). These accuracy levels were sufficient to produce graded samples that would exceed the USDA requirements. The use of color computer vision improved the accuracy of the neural networks.

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Notes

[1] Unless specified, all tables show the average accuracy of the optimal networks on the training, testing, and validating data as determined by the NeuroShell™ Optimal Network feature.
[2] Model numbers are based on the table number in which they appear and the position within the table, therefore Model 1.1 refers to the first entry in Table 1.

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