Neural network parameter effects on object classification and wavelength selection

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Abstract. A back propagative neural network (NN) was used to select visible spectrum (400 to 700 nm) wavelengths and classify damaged and undamaged peanut kernels. Results showed kernel classifications were best, network errors were minimized, and speed of convergence was greatest when the NN was set up with 20 or more hidden nodes, a momentum of 0.45 or less, and using about 1,000,000 learning events. Reflectance data in the 620 to 700-nm range were most influential in classifying kernels followed by relative reflectance in the 400 to 480-nm range. The learning rate did not affect NN performance, but higher learning rates converged more quickly. The most accurate classification performance occurred when the NN had 40 hidden nodes and a momentum of 0.45. These settings resulted in correct classification of 87.8% of all kernels. When compared to statistical means of classifying kernels using data from specific wavelengths or data from a colorimeter, the NN correctly classified about 5% and 13% more kernels, respectively.

Subject terms: neural networks; artificial intelligence; inspection; agriculture.

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1 Introduction

Visible reflectance characteristics of many agricultural commodities are used by inspectors to subjectively classify food products into edible and inedible categories. For example, in the peanut industry, inspectors visually inspect approximately 600,000 samples of farmers' stock peanuts (*Arachis hypogaea* L.) each year for damaged peanut kernels in addition to determining other quality factors. The complete inspection process includes mechanically cleaning, shelling, and sizing a 500-g sample of peanuts in preparation for the visual inspection. During this inspection, the inspector examines each peanut greater than 6.4 mm in diameter for discolorations or insect damage and all peanuts for fungal damage. Freezing temperatures, excessive heat during drying, insect damage, and fungal damage are among the factors that adversely affect peanut quality and typically result in a discoloration on the surface of the peanut kernel. The inspectors receive about two days of training before the beginning of each farmers' stock harvest season and are provided with color charts to aid in the damaged kernel classification.[1] Certain damage types, such as the presence of *Aspergillus flavus*, or excessive amounts of some damage types, such as freeze damage, can result in a reduction in the load value by about 75%.[2] Some damage sources, such as damage due to insects, provide a means for the invasion of *A. flavus* that can produce aflatoxin, a suspected carcinogen. Thus, damaged kernels must be accurately and consistently identified to ensure the seller and buyer receive or pay a fair price for the peanuts and to ensure that peanuts at risk for containing aflatoxin are accurately identified for subsequent segregation.

Previous research shows the inaccuracies in the present grading system, some of which are due to inspector subjectivity. Dowell[3] estimated that inspector subjectivity contributed to about 24% of the total error in grading peanuts. Other research shows errors associated with using visual damage assessments to segregate edible from inedible peanuts.[4] However, this visual assessment is the only method approved by the Inspection Service for detecting damage. Proper segregation by visual assessment is important to prevent mixing aflatoxin-suspect peanuts with good peanuts. When this occurs, subsequent cleanup to reduce aflatoxin to safe levels can cost about 50% of the value of the peanuts, and cleanup is becoming increasingly more difficult as consumers demand reduced tolerance levels. Thus, a means of accurately and consistently identifying damaged, or inedible, kernels in grade samples is needed.

2 Literature Review

Previous research to remove subjectivity from determining damaged kernels concentrated on measuring spectral and spatial properties of the kernels. Dowell[5] correctly classified 63%

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of the damaged and 100% of the undamaged kernels using a black-and-white machine vision system. Subsequent tests resulted in correct classification of 79% of damaged and 100% of undamaged kernels using a tristimulus colorimeter. Correct kernel classifications were 93% for damaged and 99% for undamaged when selected wavelengths between 400 and 700 nm from a spectrophotometer were used. However, since even one *A. flavus* kernel can contaminate several tons of peanuts and since undamaged kernels account for about 90% of the lot value, the classification of undamaged and damaged kernels needs further improvement. Thus, methods of classifying kernels using the full spectral curve were investigated. The Kolmogorov-Smirnov (KS) statistical test[6] can be used to determine if two curves come from the same population and was investigated but resulted in very poor kernel classifications.[5] The KS test is sensitive to peaks in the spectral curve, but is not sensitive to where the peaks occur. Visual differences between undamaged and damaged spectral curves can be noted, thus it was hypothesized that artifical intelligence techniques, such as neural networks, may aid in kernel classifications.

Neural networks (NNs) are artificial intelligence systems developed to simulate some of the organizational principles found in the human brain.[7] NNs are particularly effective when the data sets are large, expertise does not exist in analyzing the data, and the decision required is binary,[8] which is the case with classifying many agricultural commodities. Back propagation is the most common NN type[9] and was used for this research.

The variables that affect the error and the training speed of the NN are the number of learning events, learning rate, momentum, and number of nodes. The number of learning events required to train a NN varies with the problem. Too few learning events may result in inadequate learning of the training data while too many learning events may result in memorization of the training data and poor performance with new data. Learning rate determines how much of the error to propagate back into the preceding nodes and affects the speed of convergence of the network. A lower learning rate may be slow because of small weight changes, but is more accurate. A high learning rate, however, may not produce convergence. Momentum determines how much previous node weights should be changed in subsequent steps.[9] A mathematically rigorous description of a NN is given by Nelson and Illingworth[9] and Rigney and Kranzler.[10]

No single NN architecture works best for all situations and no rigid guidelines exist for selecting the optimal NN configuration or parameters. These parameters depend on the application and may be determined and optimized experimentally.

NNs are finding commercial application in such areas as canceling noise in telecommunications, mortgage risk evaluation, bomb detection at airports, process control, and component checking.[9,11] Research is ongoing in the agricultural sector to apply NNs to quality evaluation. Thai and Shewfelt[12] used NNs to link human sensory judgments to physical measurements of external color for tomatos and peaches. Zhuang and Engel[13] showed NNs can replace expert systems in such applications as herbicide selection or selecting grain marketing alternatives. Thai, Pease, and Tollner[14] used NNs to estimate green tomato maturity from x-ray computed tomography images. Whittaker, Park, and McCauley[15] used NNs to grade beef, Rigney and Kranzler[10] used NNs to grade pine tree seedlings, and Brons et al.[16] used NNs to evaluate potted plant beauty.

The success of these NN applications warrants research into the application of NNs to classify undamaged and damaged peanuts using spectral information. Thus, the objective of this research was to investigate the use of NNs to utilize all spectral information from 400 to 700 nm to classify damaged and undamaged peanut kernels and to determine which wavelengths contributed most to correct classifications.

3 Procedures

3.1 *Data Collection*

Spectral curves were obtained from approximately 600 damaged and 200 undamaged kernels selected from the 1989 and 1990 crop years. Kernels were assigned a unique identification and stored for later reference. Kernel damage was of the following types: black spots, entirely black, brown, insect holes, *A. flavus*, white mold, purple seed coats, yellow discolorations, and freeze damage. Undamaged categories consisted of visibly good redskin and blanched (skins removed) kernels. Undamaged and damaged kernels were categorized by visual inspection.

The spectral curves were collected using an X-Rite 968 reflectance spectrophotometer (X-Rite, Inc., Grandville, Michigan) that measured the percentage of spectral reflectance from 400 to 700 nm in 10-nm intervals. The spectrophotometer specifications include a 0-deg illumination angle, a 45-deg viewing angle, and an 8-mm-diam target window. CIE illuminant C, 2° observer, was used to calibrate the meter. Damaged kernel areas filled the target window in most cases. Each side of each kernel was placed by hand over the target window. Thus, a total of about 1200 spectra from damaged kernels and 400 spectra from undamaged kernels were collected, each treated as unique. If one side of a damaged kernel appeared undamaged, that spectrum was recorded as an undamaged kernel spectrum. The damaged kernel data were combined into one data set and compared to the combined undamaged redskin and blanched data set. Blanched and redskin undamaged kernels were combined to determine the effectiveness of separating all undamaged from damaged kernels. The data were stored in an ASCII file for subsequent analysis.

3.2 *Neural Network*

A back propagation NN was developed using the NeuroShell software package (Ward System Group, Inc., Frederick, Maryland). Relative reflectance at 10-nm increments was used as input to 31 nodes in the input layer. Training proceeded for 1,000,000 learning events. NeuroShell allows the number of nodes, number of layers, learning rate, learning events, and momentum to be varied. The NN was a fully connected, feed forward, supervised network with a sigmoid transfer function. The NN output threshold was set to 0.50 and the learning threshold error was set to 0.0001. However, no network errors were less than 0.035, thus convergence was considered to occur when the minimum error during the 1,000,000 learning events was reached. Error was computed as the sum of the error factor for all training data. A kernel was classified as undamaged if the NN output was greater than 0.50 and damaged otherwise. In the training set, undamaged kernels received a score of 1 while damaged kernels received a score of 0. The NN also output the contribution factor for each input node. This contribution factor indicates which nodes, or wavelengths, are most important when classifying kernels.

Thai and Shewfelt,[12] Rigney and Kranzler,[10] and Bochereau, Bourgine, and Palagos[7] showed no benefit of using more than one hidden layer. Thus, only one hidden layer was used in this study. Nelson and Illingworth[9] noted that optimal NN parameters such as learning rate, number of hidden layer nodes, and momentum must be determined experimentally. Thus, a study was designed to examine the effects of these parameters on the accuracy of classifying undamaged and damaged peanut kernels. Table 1 shows the values for each parameter tested. The NN program randomly selects one-tenth of the total data set for the test data set. Forty-four undamaged and 112 damaged kernel spectra were used for testing classification error and about 1000 damaged and 400 undamaged spectra were used for training. The accuracy of the NN when classifying the 156 kernels in the test data was compared to the classification accuracy of previous techniques reported by Dowell.[5] These techniques, which used magnitudes of and line slopes between three statistically selected wavelengths and colorimeter tristimulus values, were applied to kernels selected for the NN test data set. The classification accuracies of the colorimeter and spectrophotometer reported here and by Dowell[5] are different. The same kernels were used in all three tests reported here, but were different kernels than those used by Dowell.[5] Thus, the procedures, not the kernels, are the same as reported by Dowell.[5]

Comparisons between variables were made by calculating the least significant difference using SAS[17] statistical analysis software. The three levels of the three variables resulted in 27 possible combinations. When determining the effects of the three levels of a given variable on the classification accuracy, the results from the other variables were averaged together.

Table 1 NN variables used to classify undamaged and damaged peanut kernels. The network was trained for 1,000,000 learning events.

Number of Hidden Layer Nodes	1	20	40
Learning Rate	0.1	0.6	0.9
Momentum	0	0.45	0.9

Table 2 Comparison of three levels of three variables of a NN trained on about 400 undamaged peanut kernels and 1200 damaged kernels and used to classify 44 good kernels and 112 damaged kernels.

Variable	Undamaged Average Correct (%)¹	Damaged Average Correct (%)¹	Total Average Correct (%)¹	Minimum Network Error²
No. Nodes				
1	36.1b	92.1a	74.2a	0.05821a
20	46.9a	85.9a	73.4a	0.04947b
40	41.7ab	90.4a	74.8a	0.05012b
Learning Rate				
0.1	37.0a	91.1a	73.8a	0.05313a
0.6	43.2a	91.1a	75.7a	0.05292a
0.9	44.5a	86.3a	72.9a	0.05174a
Momentum				
0	41.8a	90.9a	75.2a	0.05154b
0.45	46.2a	88.4a	74.9a	0.05106b
0.9	36.8a	89.2a	72.4a	0.05520a

¹Means for each variable in columns followed by the same letter are not significantly different at P=0.05.
²Network error is the difference between the expected and actual outputs.

Table 3 Linear and quadratic R^2 values for each variable tested in a NN used to classify undamaged and damaged peanut kernels.

Variable	Undamaged R^2	Damaged R^2	Total¹ R^2	Minimum Network Error¹ R^2
Nodes				
Linear	0.011	0.003	0.002	0.175
Quadratic	0.042	0.046	0.008	0.258
Learning Rate				
Linear	0.022	0.021	0.001	0.005
Quadratic	0.023	0.033	0.033	0.006
Momentum				
Linear	0.009	0.003	0.031	0.037
Quadratic	0.032	0.007	0.037	0.056

¹Network error is the difference between the expected and actual outputs.

4 Results and Discussion

The best classification and smallest network error occurred when using 40 hidden layer nodes, a learning rate of 0.6, and a momentum rate of 0.45. These parameters resulted in correct classification of 87.8% of all kernels, a network error of 0.036, and convergence after 269,000 learning events. When 20 hidden layer nodes were used with the preceding parameters, 86% correct classification was achieved.

A statistical comparison of the levels of each variable showed network error decreased as the number of nodes increased to 20 and leveled off thereafter. Momentums less than 0.9 had significantly lower network errors. Learning rate did not have a significant effect on kernel classification or network error (Table 2).

Linear and quadratic lines were fit to the data to further study trends in the data. All R^2 values were less than 0.30. Thus, any one variable accounted for less than 30% of the total variation. The R^2 values increased with quadratic analysis, but are all still less than 0.30. The number of nodes received consistent benefit from the quadratic regression applied to kernel classification and network error (Table 3). This further shows, for undamaged kernels and for network error, that classification and error improve as hidden nodes increase to 20, then classification did not improve further. Thai, Pease, and Tollner[14] also noted that classification accuracy increased as the number of nodes increased to four, then accuracy decreased. Nelson and Illingworth[9] also described this quadratic effect of nodes on classification by noting that too many nodes in the hidden layers make it hard for the network to generalize. Too few hidden layer nodes lead to an inability to form adequate intermediate representations that encode significant features in the data.

A comparison of the results from this NN to previous research where kernels were classified using statistically selected wavelengths and line slopes from data obtained using a spectrophotometer and using L* a* b* color space values

Table 4 Damaged and undamaged peanut kernel classification accuracy of: (1) a neural network that utilized all wavelengths from 400 to 700 nm in 10-nm increments; (2) statistically selected line slopes and magnitudes of reflectance at 450, 520, and 670 nm; and (3) colorimeter L* a* b* values.

Method of Classification	Undamaged Correct (%)	Damaged Correct (%)	Total Correct (%)
1) Neural Network[1]	82.0	90.6	87.8
Statistics			
2) 3 wavelengths	98.0	63.2	74.4
3) Colorimeter (L*a*b*)	78.0	84.9	83.0

[1]Network parameters were nodes=40, learning rate=0.6, momentum=0.45, and trained for 1,000,000 learning events.

from a colorimeter is shown in Table 4. The procedures used to collect the data from the previous research are reported by Dowell.[5] The same kernels were used in the three current studies so direct comparisons could be made. Table 4 shows that the NN classified undamaged, damaged, and total kernels better than the colorimeter method and classified damaged and total kernels better than the three-wavelength method. Total kernel classification of the NN was about 5% better than the colorimeter method and about 13% better than the three-wavelength method. This improvement of NNs over statistical techniques is similar to those reported by Bochereau, Bourgine, and Palagos,[7] Whittaker, Park, and McCauley,[15] and Brons et al.[16]

A study of the contribution each wavelength made to the kernel classification revealed that relative reflectance of wavelengths in the 620 to 700-nm range was most influential in classifying kernels followed by reflectance in the 400 to 480-nm range (Table 5). This agrees very well with previous research[5] that statistically identified wavelengths at 430 and 690 nm as being most influential.

Future research will focus on separating the undamaged and damaged categories into subgroups including undamaged blanched, undamaged redskins, purple, black, and brown to see which categories can be predicted with the most accuracy. In addition, wavelengths selected in this research will be used to design a commercial on-line sensor to classify undamaged and damaged peanut kernels.

5 Summary

Results showed that kernel classification was best, network error minimized, and speed of convergence greatest when the NN was set up with 20 or more nodes and used with a momentum of 0.45 or less. The learning rate did not affect NN performance but did affect the speed of convergence. The most accurate kernel classification occurred when the NN parameters were set at 40 nodes, a learning rate of 0.6, and a momentum of 0.45. These parameters resulted in a minimum network error of 0.036 and 87.8% of all kernels correctly classified. Convergence occurred at 269,000 learning events for this case. When compared to statistical means of classifying kernels using data from specific wavelengths or data from a colorimeter, the NN correctly classified about 5% and 13% more kernels, respectively, than the two other methods. The wavelengths contributing most to correct kernel classification were in the 400 to 480-nm and 620 to 700-nm ranges.

Table 5 NN contribution factors[2] for each wavelength when classifying undamaged and damaged kernels. Only those tests where more than 85% of the kernels were classified correctly are included. The larger the contribution factor in a given column, the more the wavelength contributed to correct classification.

Wavelength (nm)	Test Number[1]		
	41	42	68
400	8.6	8.7	27.2
410	10.8	10.9	26.9
420	11.9	12.0	30.4
430	11.7	11.8	31.1
440	10.8	10.9	33.6
450	11.3	11.4	31.6
460	12.4	12.5	29.9
470	12.0	12.1	28.4
480	11.3	11.3	25.7
490	8.1	8.2	21.0
500	9.2	9.3	17.0
510	9.3	9.4	17.2
520	9.3	9.5	17.5
530	8.8	8.9	18.1
540	8.9	9.0	14.3
550	7.4	7.4	15.8
560	6.1	6.1	16.9
570	6.2	6.3	16.9
580	6.4	6.5	17.5
590	5.6	5.5	20.5
600	7.9	7.9	22.5
610	9.2	9.2	23.0
620	10.8	10.7	24.0
630	13.6	13.7	28.4
640	12.4	12.5	32.8
650	12.6	12.6	32.9
660	13.1	13.2	33.2
670	13.4	13.5	32.8
680	12.0	12.1	33.2
690	12.3	12.5	36.1
700	14.8	14.9	38.3
Kernels correctly classified (%)	86.5	85.9	87.8

[1]Number of hidden layer nodes >20; learning rate $= 0.6$; momentum $= 0.45$.
[2]Contribution factors show only relative contributions of wavelengths for a given test. Comparisons of contribution factors between tests of a given wavelength are not valid.

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