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Corn Kernel Shape Identification by Machine Vision Using a Neural Network Classifier

K. Liao, M. R. Paulsen, J. F. Reid, B. Ni, and E. Bonifacio

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ABSTRACT

A machine vision system capable of performing identification of corn kernel profile for shape and breakage was developed for automated grain quality inspection. The profile of corn kernel was resampled into a sequence of one-dimensional digital signals from its binary image. Shape parameters were selected by analyzing the kernel profile and were sent into a machine learning algorithm to train for a shape membership function of broken versus whole kernel status. This system provided successful classifications of 93% and 91% for whole and broken kernels, respectively.

INTRODUCTION

The profile shape of corn kernel is very important for both variety classification and quality inspection involving the detection of broken versus whole kernel status. Presently, the classification of the profile shape of corn kernel is rarely performed because it would involve tedious human inspection and would require highly trained inspectors. The inspection for corn quality, *e.g.* kernel breakage, is a very time consuming process even on relatively small 50 gram samples. Such tests will not be useful for large-scale inspection and grading unless fully automated. For a feasible automatic corn variety classification and quality inspection system, high-speed real-time classification of profile shapes of corn kernels is a fundamental requirement.

Machine vision has long been used to extract profile shape features of the grain kernel for variety classification and quality inspection. Zayas *et al.* (1985, 1986, 1989) used machine vision system to extract the morphological profile shape features and used these features to discriminate wheat classes and varieties with a correct classification rate of over 80% for most wheat varieties. They used shape features like kernel dimensions (length, width, *etc.*) and a kernel dimension-based profile shape descriptor. Lai *et al.* (1986) used similar techniques to extract morphological profile shape features from cereal grain kernels and to identify cereal seed types by their profile pattern. Sapirstein *et al.* (1987) and Neuman *et al.* (1987) classified cereal grains using the morphological profile shape features of the grain which were extracted from digitized binary images of grain. Features such as kernel geometric dimensions and Fourier spectrum profile descriptors were used as classification criteria. Ding *et al.* (1990) used a set of profile symmetry factors along the principle axis of corn kernels to classify the corn kernel breakage along the edge area. It was reported that the profile symmetry method correctly classified approximately 88% of both whole and broken kernels. Zayas *et al.* (1990) used a set of morphological parameters to discriminate whole corn kernels from broken corn kernels. Statistical discriminant functions from SAS procedures were used to perform shape discriminant analysis. The results shown that the corn kernel morphological parameters could accurately discriminate whole kernels from broken kernels.

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An accurate and reliable kernel profile shape classifier was needed. The classifier requires a relationship between profile shape features and shape categories of the kernel to learn an accurate profile shape model (concept or membership function). The relationship between shape features and shape categories is complex and not describable with one or two simple parameters or discriminant functions and the input features contain high-level background noise due to data collecting and processing procedures and are continuous real number attributes. Such a relationship would be difficult to learn using traditional statistical methods or rule-based knowledge systems.

A neural network classifier was used to learn the relationships between kernel shape features and kernel shape categories. Neural networks are capable of learning concepts that are not linearly separable and such dealing with uncertainty, noise, and random situations. Neural networks have been used to model and classify the shape differences of agricultural products. Brandon *et al.* (1990) used a counterpropagation paradigm to build a neural network classifier for carrot tip shape classification into five categories. The classifier learned from the carrot tip shape features by counterpropagation. The classifier was found to have an average misclassification rate of 11.5%. Paulsen *et al.* (1992) used the backpropagation algorithm to model the shape differences between the whole and broken corn kernels by using Fourier coefficients of the kernel profile for the crown end kernel sides as shape features. Their neural network corn kernel whole/broken classifier was built from the neural network model and had a successful classification rate of 95% for both whole and broken kernels.

OBJECTIVES

The objective of this research was to develop a neural network-based corn kernel profile shape discrimination system which could accurately classify different kernel shapes for determining broken versus whole kernel status.

MATERIALS AND METHODS

Image Acquisition

Image System: A Matrox Electronic System Ltd. Model Image-1280 real-time image processing board[1] and a Image-RTP real-time processor were used to collect images from a SONY Model XC-711 CCD RGB 768(H) x 493(V) color camera which included a C-mount adapter to support a Micro-Nikkor f/2.8 55 mm lens. The image processing board included a TMS34020 local central processing unit (CPU), a color digitizer with a resolution of 1024 x 1024 pixels with 8-bit/pixel for each RGB color component, four frame buffers with 1024 x 1024 pixels with 8-bit/pixel each, and a 64K 24-bit statistical look-up table (LUT) and an 8K 16-bit neighborhood processor LUT. The real-time processor included an arithmetic logic unit (ALU) processing element, a statistical processor, and a neighborhood processor.

The image processing board and real-time processor were installed in a Compaq 386/33 microcomputer running the OS/2 version 1.3 operating system and Microsoft C version 6.0 programming

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1. Trade names are mentioned in this publication solely for the purpose of providing specific information. Mention of a trade name, proprietary product or specific equipment or company does not constitute a guarantee or warranty by the University of Illinois and does not imply approval of the name product to the exclusion of other products that may be suitable.

language. The whole corn kernel was segmented from the background and the quality-related regions were isolated from the corn kernel by thresholding specific components of either red, green, and blue (RGB) or hue, saturation, and intensity (HSI) images. Only the green image was used in this research. Images of the kernel and the quality-related regions were binarized, labeled and stored in separate regions of interest (ROI) on the same frame buffer of the image board for further analysis.

Illumination: A cylindrical lighting chamber internally coated with a flat white enamel paint was used to provide diffuse reflected light to specimens within the chamber, Casady and Paulsen, (1989). Light was provided by two GE EYC 75W quartz halogen bulbs operated at 10.0 V DC which provided a color temperature of 3200°K. The bulbs were driven by a Brute II 600 regulated DC power supply capable of providing an output voltage deviating by less than $\pm 0.1\%$ from the set point under varying voltage input conditions of 105 to 130 V AC.

Standardization: Standardization for geometric size and for color was performed. Digital images were represented by an array of pixels. Each pixel was rectangular in shape, but was not a clearly specified size. Each pixel represents a certain amount of distance in the horizonal and vertical direction of an image. To calibrate the system, a rectangular aluminum plate, which was 1 cm x 2 cm, was placed under the camera and compared to the numbers of pixels in length, width, and area for an image of the plate. Calibration factors with units of mm/pixel were determined for the row length and column length of pixels. Similarly, a calibration factor with units of mm^2/pixel was calculated to represent the approximate area occupied by each pixel. The camera f-stop value was set to a point mid-way between 2.8 and 4 and the distance from the camera lens to the kernel surface was maintained constant at 180 mm ± 0.5 mm.

View of Objects: The view of maize kernels from a camera is limited to a fixed direction. With only one camera and fixed camera position, a machine vision system views only a limited region of the surface of a kernel. For dimension measurements, maize kernels were measured alternately with the germ side up or down. Kernels were placed individually on a dark blue background of smooth glass under the camera and were turned manually.

Kernel Profile Shape Descriptions

Based on domain knowledge of corn kernel shape related to whole or broken kernel status, 34 morphological features were selected for kernel profile shape description. These shape features of a corn kernel included 16 local maximum curvatures along the whole perimeter, 13 symmetry ratios along the major axis, 3 aspect ratios of the kernel, 1 roundness ratio of the kernel, and 1 for area in pixels of the kernel.

Local Maximum Curvatures: The corn kernel edge was sampled from binarized corn kernel images. The one-dimensional profile signal was the distance from the centroid of the kernel to the kernel edge at a constant sampling angle, $\Delta\theta$, and $\Delta\theta = 2\pi/N$, where N is the total number of sampling points along the kernel edge, Figure 1. $N = 128$ was used for the whole kernel.

The first edge sampling point was found by searching with the fast line searching Bresenham algorithm, Hegron (1988), along the direction at $\theta = 0$, which was $\pi/2$ (90°) from the longitudinal axis (major axis) of the kernel image. Then the next edge point was found by searching in the neighborhood of the previously found edge point after moving a counterclockwise angle increment of $\Delta\theta$. The sampling procedure was continued until the whole perimeter was sampled. The sampled kernel edge, p(k), was split into 16 segments starting at $k = 0$ according the initial experiment results. The curvatures at each sampling point on the kernel perimeter were calculated by the function:

$$|\kappa(k)|^2 = \left[\frac{d^2\, p_x(k)}{d\, k^2}\right]^2 + \left[\frac{d^2\, p_y(k)}{d\, k^2}\right]^2 \qquad (1)$$

Where k = 0, 1, 2, ..., N-1; $\kappa(k)$ is the curvature at the sampled edge point p(k); $p_x(k)$ and $p_y(k)$ are the x- and y-coordinate positions of the sampled edge point p(k), respectively. The 16 local maximum curvatures were found from each of the 16 kernel edge segments.

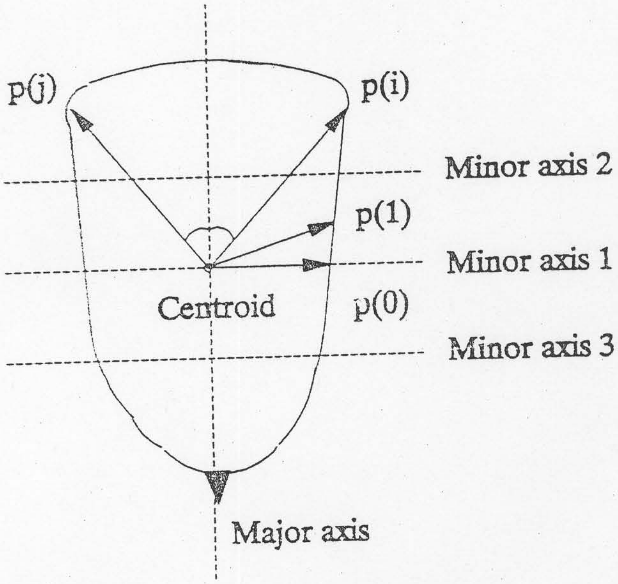

Figure 1. Corn kernel centroid, axes, and edge points sampled.

Symmetry Ratios: The symmetry ratio along the major axis was defined as the ratio of the distance from the kernel centroid to the sampled edge point i, p(i), to the distance from the kernel centroid to the sampled edge point j, p(j). The sampled edge point i and j were located on opposite sides of the major axis, respectively, and had the same angle between the major axis. Based on the initial experiment results, 13 pairs of sampled edge points were used to calculate the symmetry ratios and these points were chosen starting at k = 0 and were equally distributed towards the crown and tip cap end, respectively.

Other Shape Features: The area, aspect ratios, and roundness of a kernel were also used to describe the profile shape of the corn kernel. The kernel size was obtained directly from the object area extracted by the primitive feature extraction algorithm. The aspect ratio was defined as the ratio of the length of the major axis to the length of the minor axis which was perpendicular to the major axis. In this research, three minor axes were used. One minor axis passed through the kernel centroid, and the other two axes were located on each side of the centroid at equal distances from the centroid (approximately 1/4 of the major axis length). The roundness was defined as the ratio of the kernel area to the kernel perimeter. These features were calculated by using previously developed feature extraction algorithms (Paulsen *et al.*, 1992) and sent to the host computer as the input of a neural network classifier. The neural network classifier used was a multi-layer feed-forward network. It had one input layer, one output layer, and two hidden layers. The detailed structure of the neural network classifier is given in the following two sections.

Backpropagation (Neural Learning)

Backpropagation was used as neural learning algorithm to build the neural network classifier for corn kernel profile shape classification. Backpropagation, also called the generalized delta rule (Rumelhart *et al.*, 1986), is a well-known procedure and has been tested on several large-scale problems (Sejnowski and Rosenberg, 1987; Tesauro and Sejnowski, 1989).

The backpropagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error across all of the actual outputs of a multi-layer network and all of the desired outputs. The backpropagation training algorithm is given as follows:

Initialize all weights and node offsets to small random values;
WHILE (error > desired error) OR (epochs < assigned epochs) DO
  Present input vector and desired output vector;
  Calculate actual output vector;
  Adjust weights for all patterns (input/output pairs).

The actual output of the multi-layer network is given in Equation 2:

$$o_{pkj} = \frac{1}{1 + \exp\left(-\left(\sum_i w_{kji} o_{p(k-1)i} + \theta_{kj}\right) \right)} \qquad (2)$$

where o_{pkj} is the output of node j in layer k for pattern (input/output pair) p, $o_{p(k-1)i}$ is the output of node i in layer k-1 for pattern p, w_{kji} is the weight connecting node i in layer k-1 to the node j in layer k, θ_{kj} is a tunable threshold or bias for node j in layer k. The weights of each node are adjusted after presentation of each pattern p by backpropagating error measures layer by layer from the output back to the input according to the generalized delta rule, Rumelhart *et al.*, 1986.

The desired neural network was iteratively trained on a set of training exemplars until the tolerance range of the mean square error was reached. The neural network classifier was obtained by building a software neural network simulator from the weights of the learned network by using the relationship of Equation 2.

Corn Kernel Shape Identification

To build the neural network classifiers, 450 corn kernels from the commercial market channel were sampled as a training set. These 450 kernels included 226 whole kernels and 224 broken kernels. The whole kernels included 54 large round kernels, 37 small round kernels, 55 long flat kernels, 50 short flat kernels, and 30 small flat kernels with sharply pointed tip cap ends. The broken kernels included 104 kernels with crown tops broken, 70 kernels with longitudinal breaks, and 50 kernels with tip cap ends broken. The morphological profile shape features of each kernel were extracted both with the germ side up and with the germ side down using the real-time feature extraction algorithms and saved, associated with its shape category, into a file for future training. In this research, three neural network classifiers were built from the same training set. The neural network classifiers included whole kernel shape classifier, broken kernel shape classifier, and whole/broken kernel classifier.

Shape of Whole Kernels: Five profile shape categories were defined for the whole corn kernels. The whole kernel categories included large round kernels, small round kernels, long flat kernels, short flat kernels, and small flat kernels with sharply pointed tip cap ends. A four layer neural network (Figure 2), which had 34 input nodes (34 shape features), 5 output nodes (5 whole shape categories), 80 nodes for the first hidden layer, and 24 nodes for the second hidden layer, was trained to build the whole kernel shape classifier.

Shape of Broken Kernels: Three profile shape categories were defined for the broken corn kernels: crown tops broken, longitudinal breaks, and tip cap ends broken. The crown tops broken was the most frequently occurring broken category and included flat crown broken, angular crown broken, and minor crown damage. A four layer neural network (Figure 2), which had 34 input nodes (34 shape features), 3 output nodes (3 broken shape categories), 80 nodes for the first hidden layer, and 24 nodes for the second hidden layer, was trained to build the whole kernel shape classifier.

Whole Kernels versus Broken Kernels: For corn kernel breakage inspection, two shape categories were defined, whole and broken. A four layer neural network (Figure 2), which had 34 input nodes (34 shape features), 2 output nodes (whole and broken kernel categories), 80 nodes for the first hidden layer, and 24 nodes for the second hidden layer, was trained to build the whole kernel shape classifier.

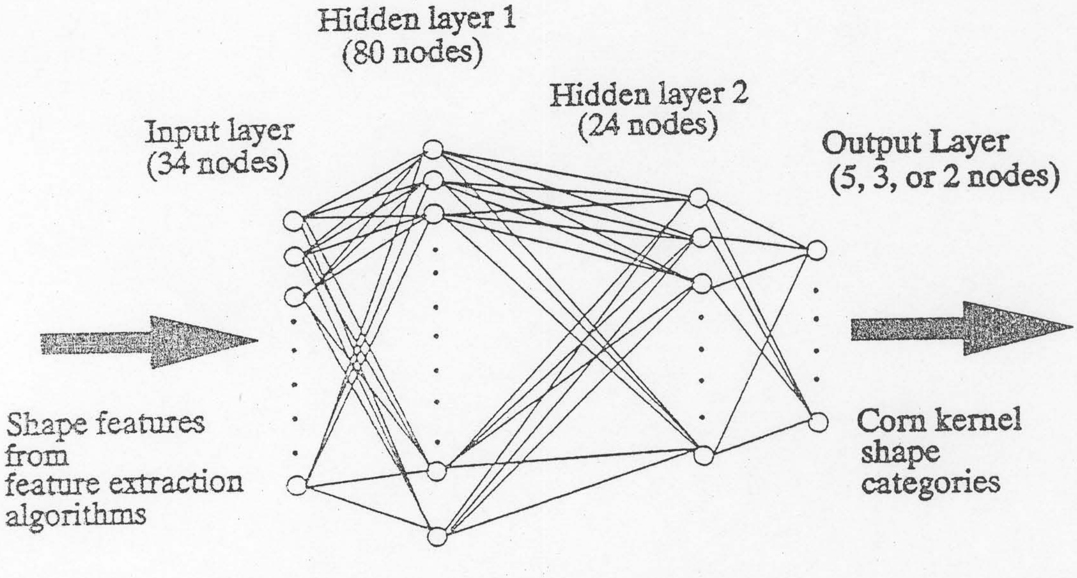

Figure 2. Neural network classifier used for corn kernel classification.

The flow chart of the neural learning and corn kernel profile shape classification procedures is given in Figure 3.

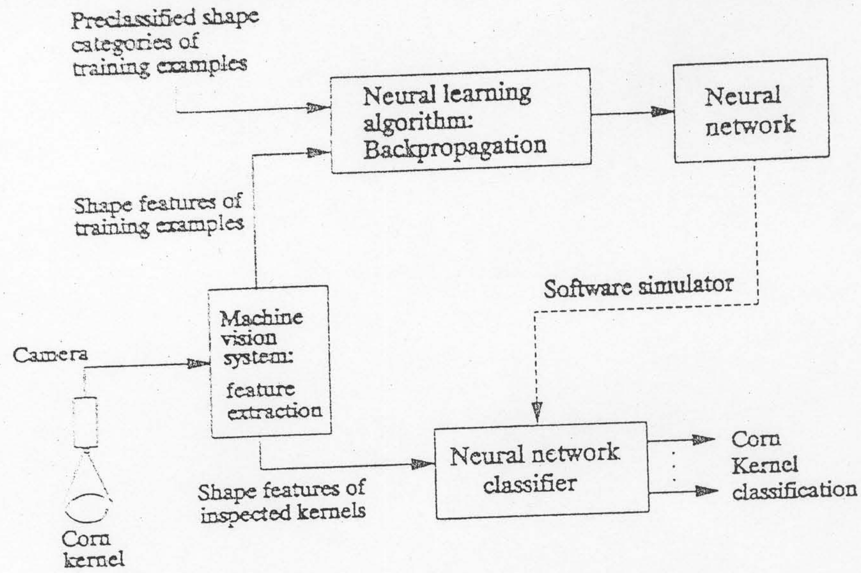

Figure 3. Procedure for neural learning and corn kernel shape classification.

RESULTS AND DISCUSSION

To test the neural network-based machine vision corn kernel profile shape classification system, three corn varieties, Variety 1, Variety 2, and Variety 3, were used in this research. Variety 1 was from an unknown hard corn variety. Variety 2 was from commercial corn samples. Variety 3 was from an unknown soft corn variety. Corn kernels were presented under the camera individually with either germ side down or up. The morphological shape features were extracted with the real-time feature extraction algorithms and put into an array as the input vector of the neural network classifier.

Shape of Whole Kernels

Whole kernels from the three corn varieties (Variety 1, Variety 2, and Variety 3) were tested using the neural network whole kernel profile shape classifier. The kernels were separated into five shape categories, large round, small round, long flat, short flat, and small flat with sharply pointed tip cap ends by a human inspector according to their profile shapes. Then, kernels were randomly selected from each shape category; and 80, 40, 80, 80, and 40 kernels were selected for the large round, small round, long flat, short flat, and small flat with sharply pointed tip cap ends shape categories, respectively. The classification results of the machine vision system are given in Table 1.

Based on the kernel profile morphological features, the whole kernel neural network profile shape classifier had an accuracy rate of 93%, 94%, 96%, 95%, and 94% for large round, small round, long flat, short flat, and small flat with sharply pointed tip cap ends for whole kernel shapes, respectively. The false classification among the shape categories was caused by the similar profile shape of a few kernels which crossed into other shape categories. For example, some kernels in the large round and short flat categories had exactly the same profile if their kernel thickness was not measured. The false classifications could be reduced by adding another camera (side view of the kernel) in the vision system and adding shape features from kernel side view to the neural network classifier.

Table 1. Accuracy of Whole Kernel Profile Shape Classification Using a Neural Network Classifier.

	LR	SR	LF	SF	SS
Variety 1:					
Classified as LR	74	0	0	0	0
Classified as SR	0	38	0	0	3
Classified as LF	1	0	77	2	0
Classified as SF	5	0	2	78	0
Classified as SS	0	2	1	0	37
Variety 2:					
Classified as LR	75	0	0	3	0
Classified as SR	0	38	0	0	1
Classified as LF	0	0	76	1	0
Classified as SF	5	0	2	76	0
Classified as SS	0	2	2	0	39
Variety 3:					
Classified as LR	74	0	0	2	0
Classified as SR	0	37	0	0	3
Classified as LF	0	0	77	3	0
Classified as SF	6	0	3	75	0
Classified as SS	0	3	0	0	37
Total classification accuracy	93%	94%	96%	95%	94%

Where : LR = large round kernels
SR = small round kernels
LF = long flat kernels
SF = short flat kernels
SS = small flat kernels with sharply pointed tip cap ends.

The processing time of the whole kernel profile shape classification was about 1.5 seconds from the live image to the final classification result.

Shape of Broken Kernels

Broken kernels from the three corn varieties (Variety 1, Variety 2, and Variety 3) were tested using the neural network broken kernel profile shape classifier. The kernels were separated by a human inspector into three shape categories, crown tops broken, longitudinal breaks, and tip cap ends broken according to their breakage characteristics. Then, kernels were randomly selected from each shape category; and 120, 80, and 40 kernels were selected for the categories of crown tops broken, longitudinal breaks, and tip cap ends broken, respectively. The classification results of the machine vision system are given in Table 2.

Based on the kernel profile morphological features, the broken kernel neural network profile shape classifier had an accuracy rate of 93%, 91%, and 92% for crown tops broken, longitudinal breaks, and tip cap ends broken kernels, respectively. The false classification among the shape categories was caused by the abnormal breakage shape which made the feature extraction algorithm fail to find the correct longitudinal axis of the kernel.

Table 2. Accuracy of Broken Kernel Profile Shape Classification Using a Neural Network Classifier.

	CTB	LB	TCB
Variety 1:			
Classified as CTB	114	5	3
Classified as LB	5	74	0
Classified as TCB	1	1	37
Variety 2:			
Classified as CTB	111	5	3
Classified as LB	6	73	3
Classified as TCB	3	2	37
Variety 3:			
Classified as CTB	110	6	4
Classified as LB	6	72	0
Classified as TCB	4	2	36
Total classification accuracy	93%	91%	92%

Where : CTB = crown tops broken
LB = longitudinal breaks
TCB = tip cap ends broken.

The processing time of the broken kernel profile shape classification was about 1.5 seconds from the live image to the final classification result.

Whole Kernels versus Broken Kernels

Samples of 180 whole and 180 broken kernels were randomly chosen from the three corn varieties (Variety 1, Variety 2, and Variety 3), and were tested using the neural network whole/broken kernel classifier. The whole kernels included an evenly distributed number of large round, small round, long flat, short flat, and small flat kernels with sharply pointed tip cap ends. The broken kernels included an evenly distributed number of kernels with crowns broken straight across the crown end, angular crown breaks, minor crown breaks, longitudinal kernel breaks, and kernels with tip cap ends broken. The classification results of the machine vision system are given in Table 3.

Based on the kernel profile morphological features, the whole/broken kernel neural network classifier had an accuracy rate of 93% and 91% for the whole and broken kernels, respectively. The false classification of whole kernels as broken was caused by the abnormal shape of some short thick kernels (particularly small thick kernels) whose profiles were very similar to those of broken pieces. The false classification of broken kernels as whole was caused by kernels with tip cap half missing, which were very similar to the whole small found kernels, and kernels with some chips missing but still had a fully intact profile. These false classifications could be reduced by considering isolation of the exposed white starch area as a broken whole parameter (it was not used in this research since it was not a shape-related parameter).

Table 3. Accuracy of Whole/Broken Corn Kernel Inspection Using a Neural Network Classifier.

	Whole kernels	Broken kernels
Variety 1:		
Classified as whole	165	17
Classified as broken	15	163
Variety 2:		
Classified as whole	169	15
Classified as broken	11	165
Variety 3:		
Classified as whole	167	16
Classified as broken	13	164
Total classification accuracy	93%	91%

The processing time of the corn kernel whole/broken inspection was about 1.5 seconds from the live image to the final classification result. The software-based neural network classifier took about 0.2 second and the time would increase with the increasing of the neural network size and structure complexity.

CONCLUSIONS

Based on the corn kernel morphological profile shape features, the neural network whole kernel shape classifier provided a successful classification of 93%, 94%, 96%, 95%, and 94% for kernels within large round, small round, long flat, short flat, and small flat with sharply pointed tip cap end shape categories, respectively. The neural network broken kernel shape classifier provided a successful classification of 93%, 91%, and 92% for kernels with crown tops broken, longitudinal breaks, and tip cap ends broken, respectively. The neural network whole/broken kernel classifier provided a successful classification of 93% and 91% for whole and broken kernels, respectively.

The processing time for each of the three classifications was about 1.5 seconds from the live image to the final classification result. The software-based neural network classifier took about 0.2 second.

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