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Determining Wheat Vitreousness Using Image Processing and a Neural Network

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Abstract. The GrainCheck 310 is a real-time, image-based wheat quality inspection machine that can replace tedious visual inspections for purity, color, and size characteristics of grains. It also has the potential for measuring the vitreousness of durum wheat. Different neural network calibration models were developed to classify vitreous and nonvitreous kernels and evaluated using samples from GIPSA and from fields in North Dakota. Model transferability between different inspection machines was also tested.

Keywords. Grading, Inspection, Automation, Machine Vision, Color

Determining Wheat Vitreousness

Using Image Processing and a Neural Network

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Durum wheat (*Triticum Durum L.*) is used by semolina millers and producers of pasta products and couscous worldwide. Approximately 100 million bushels are grown in the United States and 1.2 billion bushels are produced worldwide. Vitreousness of durum wheat is a measure of its quality and is related to the protein content. Nonvitreous (starchy) kernels are opaque and softer, and result in decreased yield of coarse semolina (Dexter et al 1988). In comparison, vitreous kernels appear hard, glassy and translucent, and have superior cooking quality and pasta color, along with coarser granulation and higher protein content. Thus, the vitreousness of durum wheat kernels is an important selection criterion in grain grading. Currently, the vitreousness of durum wheat kernels is determined by visual inspection. This method is subjective and tedious and can result in variation between inspectors. An objective grading and classification system would reduce inspector subjectivity and labor and benefit producers, grain handlers, wheat millers, and processors (Dexter and Marchylo, 2000).

In recent years, optical, mechanical, electrical, and statistical techniques have been applied to rapid grain grading and classification. Delwiche et al. (1995), using near-infrared spectroscopy (NIRS) with an artificial neural network (ANN), identified hard red winter and hard red spring wheat classes with accuracies of 95%-98%. Steenhoek et al. (2001) developed a computer vision system to evaluate blue-eye mold and germ damage in corn grading. An ANN was used in the system to achieve classifications with accuracies of 92% and 93% for sound and damaged categories, respectively. A single-kernel characterization system (SKCS 4100, Perten Instruments, Springfield, IL), which determines moisture content, weight, diameter, and hardness of individual kernels, was developed by Martin et al. (1993). Sissons et al. (2000) used the SKCS 4100 to predict kernel vitreousness and semolina mill yield. Dowell (2000) reported perfectly matched results of single kernel NIR spectroscopy with inspector classifications of obviously vitreous or nonvitreous durum wheat kernels.

The GrainCheck 310 (FOSS Tecator, Höganäs, Sweden)[1] is an image processing and ANN based instrument for assessing grain quality using color and shape information. This technology can provide real-time wheat quality inspection for every shipment of grain between producers, receiving stations, mills, and breweries (Svensson et al., 1996). It can replace tedious visual inspections of purity, color, and size characteristics and improve grading consistency. Since the GrainCheck 310 provides data related to purity and color, it should be possible to measure the kernel vitreousness.

The objective of this research was to develop neural-network models using kernel images to determine the vitreousness of durum wheat using the GrainCheck 310.

Equipment and Procedures

Equipment

[1] Mention of a firm or a trade product does not imply endorsement or recommendation of the authors over other firms or products not mentioned.

The GrainCheck 310 consisted of a kernel feeder unit, a color imaging unit, a weighing and sorting unit, and a computer (Figure 1).

Kernel feeder unit

The kernel feeder unit delivered the kernels into the field of view of a CCD camera. Grain kernels were fed from the sample inlet onto a conveyor belt, which moved forward by steps, with grooves perpendicular to the moving direction. To prevent kernels from overlapping, the belt was vibrated so that the kernels were evenly distributed over the grooves. A control unit inside the kernel feeder controlled movement of the conveyer belt and sent the distance signal of belt movement to the computer to synchronize the camera operation so that all kernels in a sample were "seen" only once by the camera. For a good contrast between the kernels and the background, a blue belt was used.

Color imaging unit

A Sony color CCD camera (512×512) was mounted 19.05 cm above the conveyer belt. One pixel represented 0.0913 mm × 0.0869 mm on the real kernel. A frame grabber board was installed in a PC where the image taken by the camera was digitized and processed. The field of view of the camera covered 7 grooves on the belt. On average, 15 kernels were processed per image. A circular fluorescent lamp was used as the illumination source of the system. It had a 20.32 cm outside diameter and emits light within the full visible wavelength range. The CCD camera was situated at the center of this circular lamp.

Personal Computer (PC)

A 100MHz Pentium PC with a frame grabber card was used to digitize the original image, conduct image segmentation and feature extraction, execute the classification algorithm based on the ANN, and serve as a user interface.

Classification Algorithm

Preprocessing

Kernels were localized in the digitized image by scanning the whole image and color-thresholding pixels against the blue background, i.e. the conveyor belt. When a non-blue pixel was found, its adjacent pixels were then examined. If an adjacent pixel was a non-blue pixel, it was considered a part of a kernel and its adjacent pixels were examined in the same way. When all pixels in the digitized image were examined, the size, the major axis, and the "center of gravity" of each kernel were determined. Each kernel was then placed in a segmented image with its major axis being horizontal and the "center of gravity" coinciding with the center of the segmented image. The width of the localized objects was used to find whether there were two or more kernels in a segmented image, as in cases where kernels were touching or overlapping.

ANN

A back-propagation network architecture was used since it is the most robust and common network. The number of inputs of the network was equal to the number of features used for classification, whereas the number of outputs was equal to the number of classes to be separated. In the back propagation algorithm, which was based on a gradient descent method, each node in a layer was connected to all nodes in the previous and the next layer with a weight. These weights defined the relationship between the image features and output classes. These weights were adapted through calibration of the training data in a step-wise manner by repeatedly presenting the data to ANN for a number of epochs so as to minimize the classification errors. Once the weights were determined, the ANN could be used to categorize samples that were not included in the calibration process.

Color images were transformed to the Hue, Saturation and Intensity (HSI) color space. To reduce the ANN inputs, four features extracted from each row and each column were projected onto an input vector x. The features extracted from image row *i* were calculated using Equations (1)-(4):

$$x_i = \sum_{j=0}^{N_c-1} \cos H(i,j) \qquad (1)$$

$$x_{N_r+i} = \sum_{j=0}^{N_c-1} S(i,j) \qquad (2)$$

$$x_{2N_r+i} = \sum_{j=0}^{N_c-1} I(i,j) \qquad (3)$$

$$x_{3N_r+i} = \sum_{j=0}^{N_c-1} \sin H(i,j) \qquad (4)$$

The features extracted from image column *j* were projected onto the input vector x using Equations (5) – (8):

$$x_{j+4N_r} = \sum_{i=0}^{N_r-1} \cos H(i,j) \qquad (5)$$

$$x_{j+4N_r+N_c} = \sum_{i=0}^{N_r-1} S(i,j) \qquad (6)$$

$$x_{j+4N_r+2N_c} = \sum_{i=0}^{N_r-1} I(i,j) \qquad (7)$$

$$x_{j+4N_r+3N_c} = \sum_{i=0}^{N_r-1} \sin H(i,j) \qquad (8)$$

where

$H(i, j)$, $S(i, j)$ and $I(i, j)$ – hue, saturation, and intensity of the pixel in row i, column j,

N_r – number of rows in the image,

N_c – number of columns in the image,

i – pixel row number, and

j – pixel column number.

Each segmented kernel image was placed in the center of a window of 70 rows by 200 columns in order to make all the images have the same size. Because each row or each column was projected onto the input vector x as four nodes, the total number of input nodes in the vector was $4(N_r+N_c) = 1080$. These input nodes represented the extracted features for a single kernel image. The value of each ANN output node represented the predicted probability that a kernel belongs to a specific output class. The kernel was assigned to the output class that had the highest predicted probability.

Experimental Design

Four sets of experiments were conducted to develop prediction models for wheat vitreousness using the GrainCheck 310. The first experiment was intended to select the most effective ANN model with respect to number of output classes, number of hidden layer nodes, and number of training epochs. The second experiment was designed to test the sensitivity of the calibration model to individual sample classes. The third experiment was an instrument-consistency test, with the objective of testing model exchangeability between two GrainCheck 310 machines. Finally, field samples were tested to evaluate performance of the selected ANN model.

<u>Sample preparation</u>

The Grain Inspection, Packers, and Stockyards Administration (GIPSA) of USDA provided three sets of test samples for this study. Sample set 1 was used to develop the calibration and prediction model for vitreousness of durum wheat. The samples were classified as “hard vitreous and of amber color” (HVAC) or “not hard vitreous and of amber color” (NHVAC) by visual inspection of the Board of Appeals and Review (BAR). Three subclasses for HVAC and six subclasses for NHVAC kernels are defined in Table 1. Figure 2 shows examples of kernel images.

Sample set 1 included 100g samples for each subclass. During the tests, each subclass was evenly divided into two sets, a calibration set and a validation set. Hence, the validation set came from the same lot as the calibration samples. The calibration set was used to calibrate the ANN prediction model, whereas the validation set was used to test the model performance.

Sample set 2 was used to assess repeatability of the calibration models on different GrainCheck 310 machines. There were 25 samples in this set. The percentage of HVAC in each sample was determined by the BAR.

Sample set 3 included 143 Durum wheat samples from Brian Sorensen, North Dakota State University. All samples weighed 100 g. The percentage of HVAC was determined by the BAR and by inspectors in North Dakota. This set was used to test the performance of the calibration model using an independent set of samples.

ANN model selection test

Three sets of calibration models were developed. This included an 11-class model, two 3-class models, and three 2-class models. Several sub-sample sets with different combinations of HVAC and NHVAC subclasses were generated to develop different calibration models. The classification rates (Equation 1) from different models were evaluated and compared.

$$\text{Classification rate of Class A} = \frac{\text{Number of kernels classified to Class A}}{\text{Total number of Class A kernels}} \qquad (1)$$

1. 11-class model

   The 11-class model was developed to classify kernels into 11 kernel classes, (Table 1), including the nine subclasses defined by BAR, a "Clip" subclass, and an "Unknown" subclass. The Clip subclass (Figure 2) included images that were clipped during segmentation and images of kernels that were not totally in the field of view. Images containing multiple kernels were classified into the Unknown subclass.

2. 3-class model

   Two 3-class models were tested.

   a. 3-class model with an Unknown class (Model 3a)

      To develop this model, all HVAC subclasses were combined into one class of HVAC (3864 images), while all NHVAC subclasses were combined into one class of NHVAC

(8494 images). The third class ("Unknown") combined the Clip and Unknown subclasses (1056 images).

b. 3-class model with a mottled class (Model 3b)

Mottling was a small, nonvitreous area in a kernel (Figure 2). Thus, mottled kernels should be considered nonvitreous. However, for most mottled kernels, mottling occurs only on a portion of the kernel and other areas on the same kernel might appear to be vitreous. On the GrainCheck 310 machine, due to the random orientation of the kernels on the conveyer belt, mottled areas might not always be exposed to the field of view of the camera. As a result, a considerable number of mottled kernels could be misclassified as vitreous kernels. To derive a possible solution to correct this misclassification, model 3b was established using three classes - HVAC, NHVAC, and Mottled. In order to balance the number of samples for vitreous and nonvitreous classes, 3600, 3000, and 600 kernels were randomly selected for the HVAC and NHVAC, and Mottled classes, respectively.

3. 2-class models

To construct a simple calibration model, three 2-class models were tested. These models classified kernel images as either HVAC or NHVAC. The difference among these models was the number of samples of each class used in training.

The first 2-class model (Model 2a) was developed using the entire original calibration image sets for HVAC and NHVAC. The sample size of NHVAC (8494 images) is about twice that of the HVAC (3864 images). The second 2-class model (Model 2b) used identical sample sizes (1900 images) for HVAC and NHVAC. These images were randomly selected from the original calibration image sets.

Considering the fact that most field samples contained mostly HVAC-01 and NHVAC-01 kernels, subclasses used for the third 2-class model (Model 2c) were weighted as described in Table 2. The total numbers for the HVAC and NHVAC classes (1500 images each) were balanced for this model.

Sensitivity test

The objective of this test was to study sensitivities of the classification model to individual subclasses. After this study, the subclasses to which the models are least sensitive may possibly be eliminated from the calibration set. Sample set 1 was used in this test. During the tests, subclasses in the calibration image set were removed one at a time to generate different models. These models were then tested using the verification sample set.

Instrument consistency test

The objective of the instrument-consistency test was to examine the exchangeability of the model across two GrainCheck 310 instruments in the laboratory. Sample set 2 was used for these tests. The model used was Model 2b with 50 nodes and 100 epochs. Results from the two machines were compared. These results were also compared with BAR inspection and re-inspection results.

Field Tests

Sample set 3 was used for field tests. The percentage of HVAC kernels in a sample was evaluated using two GrainCheck310's independently. Results from the two machines were compared to each other. These results were also compared with BAR results and with inspections obtained from the field.

Results and Discussion

ANN model selection test

1. 11-class model

   The calibration results of the 11-class model with different numbers of hidden layer nodes shows that a larger number of hidden-layer nodes yielded faster model convergence. Table 3 shows results from the tests using the validation data set. The model with 10 epochs and 200 nodes had the highest classification rates of 87.0% and 88.8% for HVAC and NHVAC, respectively. However, differences in classification rates among models with different numbers of hidden layer nodes and different number of epochs were in general not significant.

2. 3-class model

   a. 3-class model with the Unknown class (Model 3a)

      Calibration results show that the best 3a model was with 100 nodes and 100 epochs, which produced classification rates of greater than 98.0% for all three classes (Figure 3). Verification results show that the best 3a model was with 100 nodes and 70 epochs, which produced classification rates of 90.1%, 85.0%, and 55.8% for HVAC, NHVAC, and Unknown, respectively. The Unknown class included all clipped images and unknown images, which were very difficult to identify as one class with the ANN. Inclusion of the “unknown” class might also have reduced the classification rates of the other two classes. Therefore, the Unknown class was removed from other classification models.

b. 3-class model with the Mottled class (Model 3b)

For calibration, classification rates were over 96% for all 3 classes with 50 and 100 hidden layer nodes when the number of epochs was larger than 100 (Figure 4). The verification results show that the best 3b model was with 50 nodes and 120 epochs, which produced classification rates of 88.7%, 86.5%, and 73.3% for HVAC, NHVAC, and Mottled, respectively. Among the mottled kernels, 17.7% were misclassified as HVAC and 9% as NHVAC.

A visual examination of the mottled kernels randomly selected from the calibration set showed that about 22% of the mottled kernels were not positioned with the mottling facing the camera. This percentage was similar to the percentage of the mottled kernels misclassified as HVAC (17.7%) derived in the verification test. If we assume that this misclassification was mainly due to kernel orientation, a correction can be made by adding 17.7% to the number of kernels classified as Mottled. Applying this correction to the results of the verification test, the classification accuracy for the Mottled class can be improved to 91.0%. Furthermore, if the NHVAC and Mottled classes were combined into one class, the classification rate for the NHVAC class would be improved to 89.4% with the correction (Table 4).

3. 2-class Model

Different combinations of number of epochs and number of hidden layer nodes were tested for Model 2a, 2b, and 2c. For Model 2a, the best results were achieved with 100 hidden layer nodes and 100 epochs (data not shown). Classification results for the validation data set were 81.9% and 91.5% for HVAC and NHVAC (Table 4), respectively. The NHVAC class has a larger sample size than the HVAC class, which might have given a slight advantage to the NHVAC class.

For Model 2b, the best results were achieved with 50 nodes and 100 epochs (data not shown). For the validation data set, classification rates were 84.9% and 90.5% for HVAC and NHVAC, respectively (Table 4). Figure 5 shows the classification rate for each subclass. HVAC-01 and NHVAC-01 had higher classification rates (around 90%) than most other subclasses, except NHVAC-05 and NHVAC-06.

For Model 2c, the best results were achieved with 50 hidden layer nodes and 100 epochs (data not shown). For the validation data set, the classification rates were improved to 87.6% and 91.6% for HVAC and NHVAC, respectively (Table 5).

For commercial grain grading, it is often important to identify different grain-damage types, such as bleached, mottled/chalky, and sprouted kernels. The classification rate of each individual subclass should, therefore, be considered when evaluating calibration models. Based on USDA GIPSA recommendations, the subclasses HVAC-02 (Bleached HVAC Durum kernels), NHVAC-02 (Bleached NHVAC kernels), NHVAC-03 (Mottled/Chalky Durum kernels inspected as NHVAC), and NHVAC-04 (Sprouted Durum kernels inspected as NHVAC) should have classification rates of greater than 85%. Model 2a approached this accuracy for the four subclasses, but had low HVAC accuracy (81.9%). Several models exceeds 85% average accuracy for HVAC and NHVAC, but none exceeded 85% accuracy for HVAC-02, NHVAC-02, NHVAC-03, and NHVAC-04 while maintained 85% or greater average HVAC and NHVAC accuracy.

Sensitivity test

The sensitivity analysis showed that the classification accuracy always decreased when a subclass was removed from the calibration model. Thus there was no subclass that was confusing the calibration model and all subclasses should be included in calibration.

Instrument consistency test

Model 2b was used to test sample set 2 for consistency across two GrainCheck 310 machines, GC310(1) and GC310(2). The results showed the percentages of HVAC kernels in a sample, which were compared with BAR results (Figure 6). The average error was calculated by averaging the differences between results from each GrainCheck 310 machines and BAR results. The GC310's consistently underpredicted the BAR values by 12 – 15%. The average difference between the two GC310's was 1.54% (R^2 = 0.89), whereas the average difference between the original BAR inspection and the BAR re-inspection was 2.24% (R^2 = 0.85) (Figure 7). Thus, the consistency between the two GrainCheck 310 instruments was slightly better than between BAR inspections.

Field sample tests

In this test, Model 2b was verified using sample set 3. Results from the two GrainCheck 310's showed a high degree of consistency, with an average difference of 0.8% between results from the two machines and an R^2 of 0.81. However, both GrainCheck 310's underpredicted the BAR results by 15% to 16%, (R^2 = 0.63 to 0.69). One possible reason for this underprediction might be the difference in quality between the samples used to train the ANN model and the field samples used in verification. For example, the HVAC training samples used to develop Model 2b were vitreous wheat kernels with high quality in color, roundness and shape. In contrast, HVAC field samples included many aged, dry HVAC kernels. This may have confused the ANN during classification. To improve the accuracy of HVAC classification, training samples at different quality levels should be included.

The results of two GrainCheck 310 machines were also compared with the results of two manual inspections – the BAR inspection and an inspection provided by wheat-quality extension specialists at the Department of Cereal and Food Sciences at North Dakota State University. The average difference between the two manual inspections was 1.8% (R^2 = 0.75), whereas the average difference between the two machines was 0.8% (R^2 = 0.81). Thus, the machines tend to be more consistent than human inspectors.

Summary and Conclusions

1. An image–based grain-grading system that used a neural network classifier was used to classify durum wheat vitreousness.

2. Several ANN calibration models with various combinations of number of classes, number of hidden layer nodes, and number of training epochs were developed and evaluated. Samples of three subclasses of HVAC and six subclasses of NHVAC were used for model calibration and validation. Several models approached 85-90% correct classification for average HVAC and NHVAC. However, none of the models reached the correct classification rate of 85% (GIPSA criteria) for bleached, mottled, and sprout kernels.
3. A 3-class model, which included a Mottled class, was evaluated in order to minimize the effect of kernel orientation on classification. A correction method was developed to improve the classification rates. With this correction, the classification accuracies for the Mottled class and the overall NHVAC class were improved to 91.0% and 89.4%, respectively.
4. A sensitivity test proved that all subclasses of HVAC and NHVAC were significantly affecting the overall classification accuracy and none of the subclasses should be removed from the calibration sample set.
5. A 2-class calibration model was examined on two GrainCheck 310 machines to examine the transferability of the model across machines. The average classification error between the two 310 machines was 1.5% ($R^2 = 0.9$).
6. Field samples were examined by two GrainCheck 310 machines and two human inspectors. To improve classification accuracy of the GrainCheck 310's, samples at different quality levels and with different ages should be used in training. Cross-examination also indicated that the machines tend to be more consistent than human inspectors.
7. No single model provided best for all subclasses. The 2-class models may be preferred for simplicity of calibration, but additional input from GIPSA and industry is needed to determine which model may be the best for future testing.

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Table 1 Durum wheat subclass and sample definitions

No	Sample Identifier	Description	Sample Size
1	HVAC-01	Clean Durum kernels inspected as HVAC[1]	1384
2	HVAC-02	Bleached Durum kernels inspected as HVAC	1256
3	HVAC-03	Cracked or checked Durum kernels inspected as HVAC	1224
4	NHVAC-01	Clean Durum kernels inspected as NHVAC[2]	1630
5	NHVAC-02	Bleached Durum kernels inspected as NHVAC	873
6	NHVAC-03	Mottled/chalky Durum kernels inspected as NHVAC	1084
7	NHVAC-04	Sprouted Durum kernels inspected as NHVAC	1434
8	NHVAC-05	Foreign materials	1914
9	NHVAC-06	All other classes of wheat	1559
10	Clip	Clipped images of kernels	534
11	Unknown	Unknown classes	522

[1] Hard vitreous and of amber color

[2] Not hard vitreous and of amber color

Table 2. Kernel classes used for the 2-class model with weighted sample size

Class	Sample Identifier	Weight of sample size	Sample size
HVAC	HVAC-01	80%	1200
HVAC	HVAC-02	10%	150
HVAC	HVAC-03	10%	150
NHVAC	NHVAC-01	80%	1200
NHVAC	NHVAC-02	4%	60
NHVAC	NHVAC-03	4%	60
NHVAC	NHVAC-04	4%	60
NHVAC	NHVAC-05	4%	60
NHVAC	NHVAC-06	4%	60

Table 3. Validation results of classification rates (%) for the 11-class model

		Number of epochs				
Number of nodes		**10**	**100**	**200**	**300**	**450**
25	HVAC	85.6	83.2	83.1	82.3	N/A
	NHVAC	88.0	87.8	86.2	87.2	N/A
50	HVAC	80.5	83.8	84.8	83.7	82.8
	NHVAC	89.5	87.7	87.6	87.5	87.7
100	HVAC	83.9	85.8	85.3	85.0	85.4
	NHVAC	89.4	88.1	88.4	88.4	88.2
200	HVAC	87.0	85.1	85.9	85.7	N/A
	NHVAC	88.8	88.4	88.5	88.7	N/A
300	HVAC	83.9	86.7	86.7	86.0	86.2
	NHVAC	90.0	88.4	88.6	89.1	83.7

Table 4. Accuracy of predicting vitreousness of durum wheat using various neural network models

Classes	HVAC Average	NHVAC Average	HVAC 01	HVAC 02	HVAC 03	NHVAC 01	NHVAC 02	NHVAC 03	NHVAC 04	NHVAC 05	NHVAC 06
11 Class[1]	87.0	88.8	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
3a Class[2]	90.1	85.0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
3b Class[3]	88.7	86.5	93.6	90.4	82.3	85.1	75.4	82.3	85.2	92.9	97.9
3c Class[4]	88.7	89.4	93.6	90.4	82.3	85.1	75.4	100.0	85.2	92.9	97.9
2a Class[5]	81.9	91.5	90.9	82.9	71.9	88.6	82.0	86.3	95.0	98.3	98.7
2b Class[6]	84.9	90.5	90.9	88.1	70.4	89.8	77.6	83.0	89.6	96.6	98.3
2c Class[7]	87.6	91.6	95.4	86.1	66.7	88.8	79.5	76.3	74.7	88.6	95.3

Note:

[1]The 11 classes include all HVAC and NHVAC subclasses, plus clipped and unknown images

[2]HVAC, NHVAC, and Unknown classes

[3]HVAC, NHVAC, and Mottled classes

[4]HVAC, NHVAC, and Mottled classes, with correction for mottling

[5]HVAC and NHVAC classes. Unequal sample sizes

[6]HVAC and NHVAC. Equal sample sizes

[7]HVAC and NHVAC classes. Weighted sample sizes

N/A: The 11-class model and Model 3a were only tested for HVAC and NHVAC. Data for individual subclasses was not available.

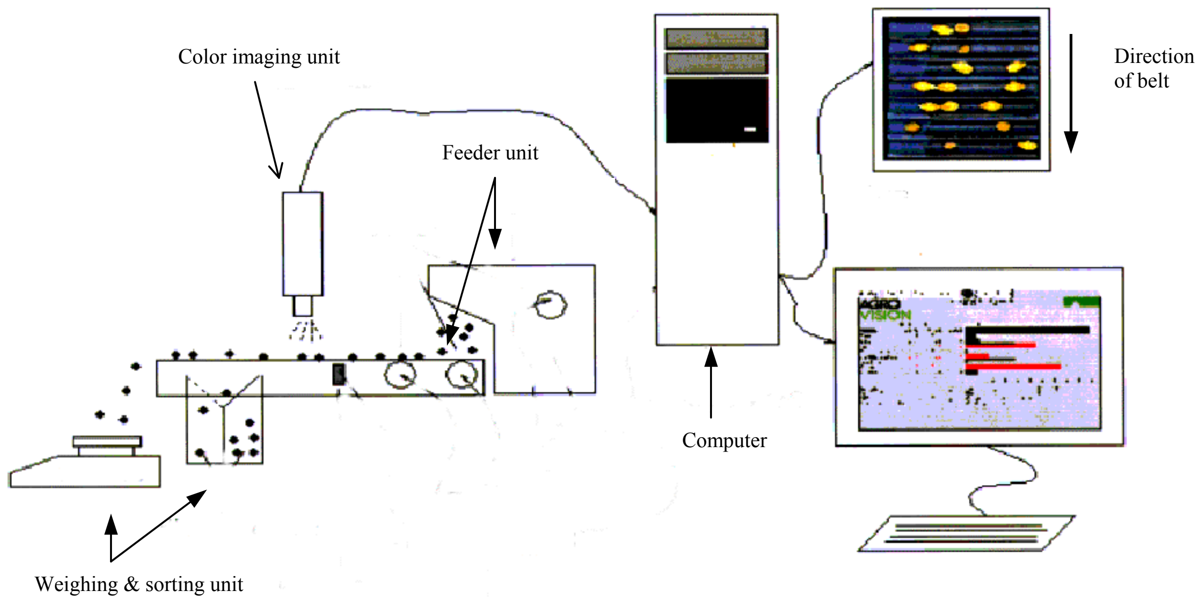

Figure 1. System Configuration

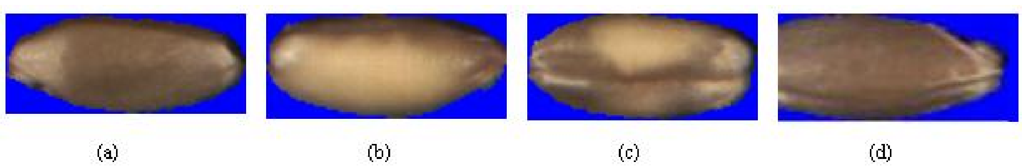

Figure 2 Kernel images for (a) HVAC01, (b) NHVAC01, (c) Mottled, and (d) Clip

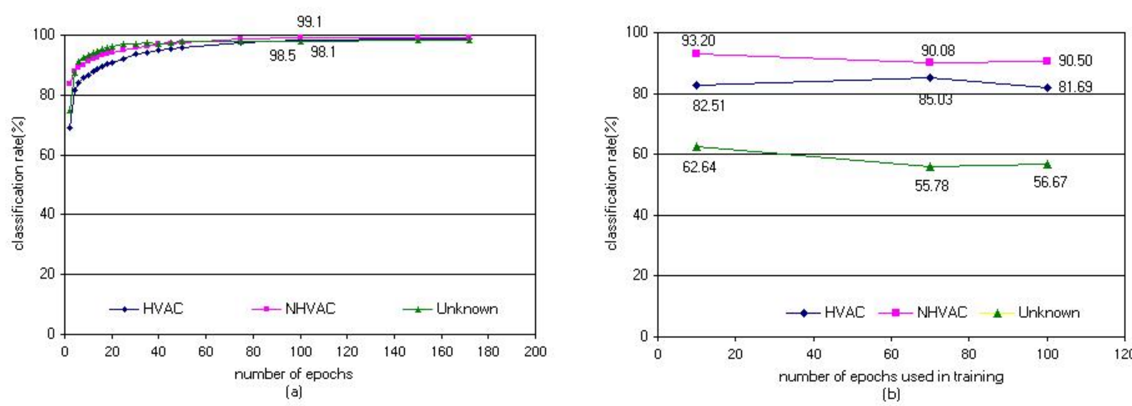

Figure 3. Calibration and validation results for the 3-class model (a) Calibration result of 3-class model with 100 hidden layer nodes (b) Validation result of 3-class model with 100 hidden layer nodes

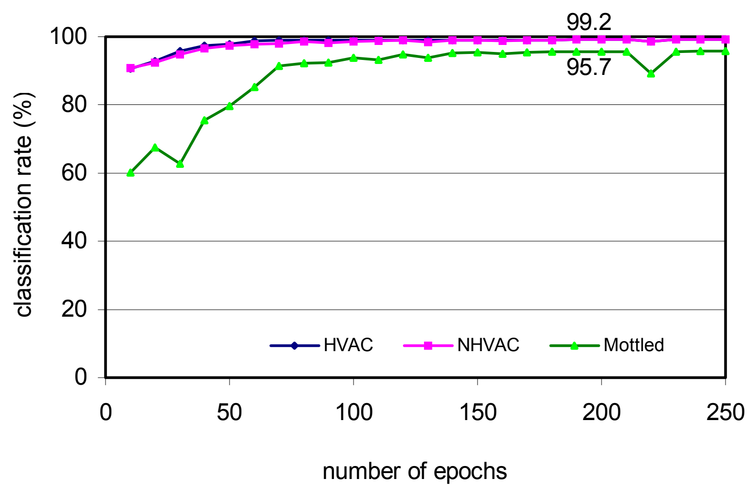

Figure 4. Calibration results for the 3-class model with Mottled class and with 50 hidden layer nodes

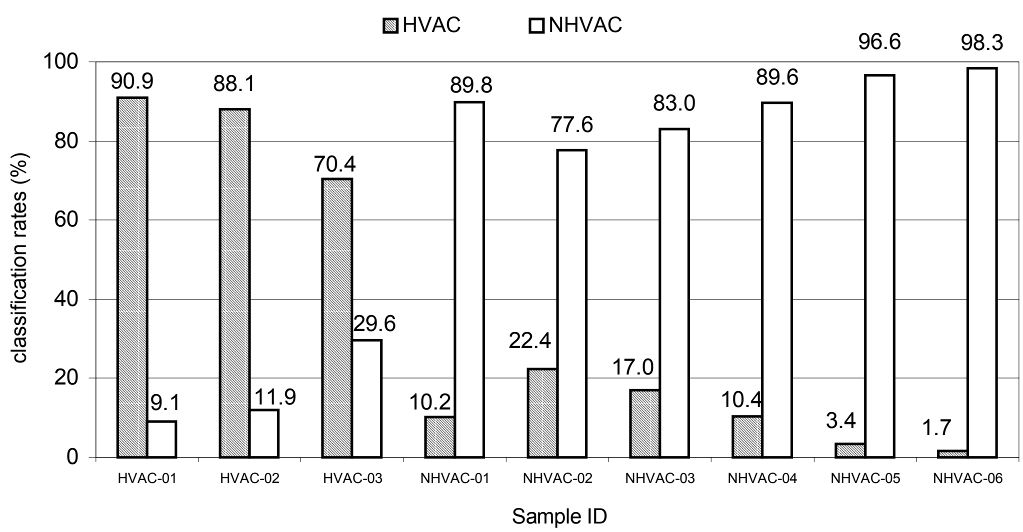

Figure 5 Classification rate of each subclass using Model 2b with 100 nodes and 50 epochs

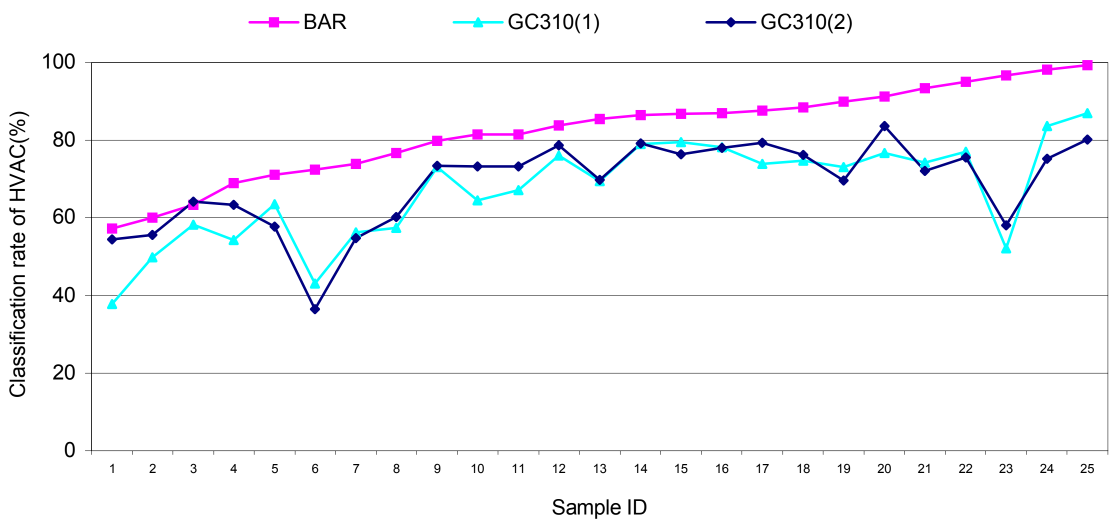

Figure 6. Comparison of results obtained from two GrainCheck 310's and from the BAR examinations, using sample set 2

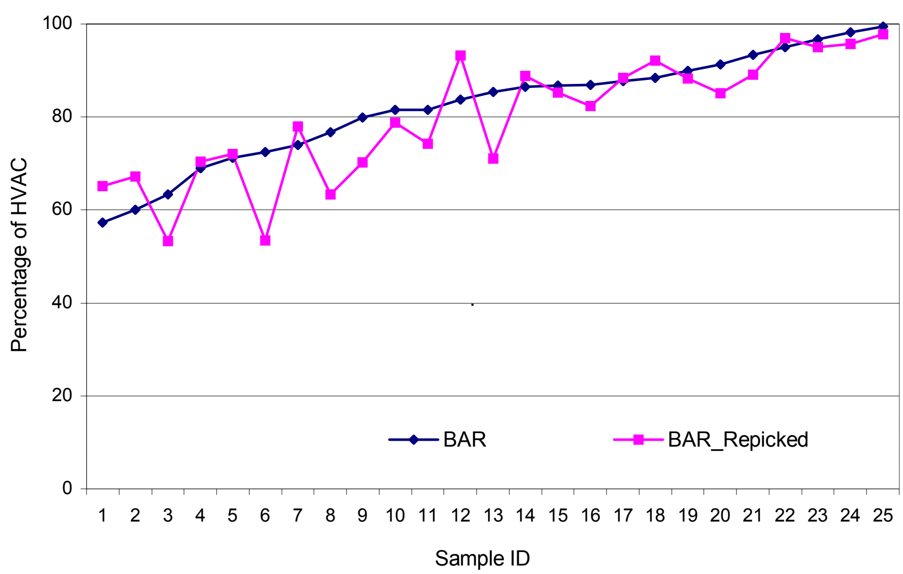

Figure 7. Comparison of results obtained two BAR examinations