
Comparison of two neural network architectures for classification of singulated cereal grains

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¹*Department of Biosystems Engineering, University of Manitoba, Winnipeg, Manitoba, Canada R3T 5V6; and* ²*Cereal Research Centre, Agriculture and Agri-Food Canada, 195 Dafoe Road, Winnipeg, Manitoba, Canada R3T 2M9*

Visen, N.S., Jayas, D.S., Paliwal, J. and White, N.D.G. 2004. **Comparison of two neural network architectures for classification of singulated cereal grains.** *Canadian Biosystems Engineering/Le génie des biosystèmes au Canada* 46: 3.7 - 3.14. A digital image analysis algorithm was developed to facilitate classification of individual cereal grain kernels (barley, Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, and rye). A total of 230 features (51 morphological, 123 color, and 56 textural) were extracted from 7500 high resolution color images of each type of grain using the developed algorithm. A four-layer back-propagation neural network (BPN) and a specialist probabilistic neural network (SPNN) were evaluated for classification accuracies. The BPN used a sigmoid scaling function for input nodes and sigmoid activation function for nodes in the hidden layers. Five different data sets were used for training, testing, and validation. The BPN based classifier outperformed the SPNN classifier for all grain types. Using various features models, the average classification accuracies for BPN were 96.4, 90.8, 98.0, 95.5, and 96.4% for barley, CWAD wheat, CWRS wheat, oats, and rye, respectively. For the SPNN classifier, the average classification accuracies were, 91.5, 84.7, 95.3, 88.4, and 93.3% for barley, CWAD wheat, CWRS wheat, oats, and rye, respectively. **Keywords:** machine vision, neural networks, cereal classification, digital image processing, wheat, barley, rye, oats.

Un algorithme d'analyse d'image digitale a été développé pour faciliter la classification de grains individuels de céréales (orge, blé Canada Western Amber Durum (CWAD), blé Canada Western Red Spring (CWRS), avoine et seigle). Un total de 230 caractéristiques (morphologie (51), couleur (123) et texture (56)) ont été extraites de 7500 images couleurs à hautes résolutions pour chaque type de grains utilisés dans l'algorithme développé. Un réseau neuronal de propagation à quatre couches (NP) et un réseau neuronal probabilistique spécialisé (NPS) ont été évalués sur leur précision de classification. Le NP utilisait une fonction d'échelle sigmoïde pour les nœuds d'entrées et une fonction d'activation sigmoïde pour les nœuds des couches sous jacentes. Cinq différents groupes de données ont été utilisés pour l'entraînement, le testage et la validation. Le classificateur basé sur le NP a dépassé les performances du classificateur NPS pour tous les types de grains. En utilisant les différents modèles disponibles, les précisions moyennes de classification pour le NP étaient respectivement de 91,5, 84,7, 95,3, 88,4 et 93,3% pour l'orge, le blé CWAD, le blé CWRS, l'avoine et le seigle. **Mots clés:** vision artificielle, réseaux de neurones, classification de céréales, analyse par image digitale, blé, orge, seigle, avoine.

INTRODUCTION

Machine vision systems (MVS) provide an alternative to manual inspection of grain samples for determining characteristic kernel properties and the amount of foreign material in a sample.

During grain handling operations, information on grain type and grain quality is required at several stages before the next stage of storage and handling. In the present grain-handling system, grain type and quality are rapidly assessed by visual inspection. This evaluation process is, however, subjective and is limited by the experience and expertise of the individual. The decision-making capabilities of a grain inspector can be seriously affected by his/her physical condition, such as fatigue and eyesight, mental state caused by biases and work pressure, working conditions such as improper lighting, and other environmental conditions.

Determining the potential of morphological features to classify different grain species, classes, varieties, damaged grains, and impurities using a statistical pattern-recognition technique has been the main focus of the published research (e.g., Neuman et al. 1987; Keefe 1992; Sapirstein and Kohler 1995; Utku and Koksels 1998; Majumdar and Jayas 1999, 2000a). Some researchers (e.g., Neuman et al. 1989a, 1989b; Luo et al. 1999a; Majumdar and Jayas 2000b; Ruan et al. 2001) have used color features for grain identification, but variability in the illumination of common light sources poses a practical problem. Only limited work has been done to incorporate textural features (e.g., Majumdar et al. 1996; Ruan et al. 1998; Majumdar and Jayas 2000c, 2000d) for classification purposes. Efforts also have been made to integrate all these features in terms of a single classification vector (Paliwal et al. 1999) for grain kernel identification.

Most of the available algorithms use the kernel size for classification purposes. Use of size can result in significant misclassifications because the variations in kernel size depend on maturity and growing conditions. Because the grain at a grain-handling facility is a mixture of grain coming from different farm locations, size variability can give erroneous results. Currently, available algorithms extract a large number of features and use them for classification. Extraction and comparison of a large number of parameters increase the computation time. For any system to be used on an industrial scale, operational speed is a constraining factor.

The objectives of this research were to develop and optimize a technique for discrimination of various types of grains by extracting the morphological-, texture-, and color-based features using images of single kernels and compare the classification accuracies using back propagation and specialist probabilistic neural network classifiers.



Fig. 1. Image acquisition system (left) and illumination system (right).

MATERIALS and METHODS

Grain samples

The grain samples used in this study were collected from six locations in Manitoba, ten locations in Saskatchewan, and seven locations in Alberta. The Industry Services Division of the Canadian Grain Commission (Winnipeg, MB) provided the grain samples which were collected at terminal elevators from incoming railcars. The choice of locations was based on climatic subdivisions of the Canadian Prairies (Putnam and Putnam 1970). The selected locations represent five sample locations from the humid prairie, five locations from the semi-arid region, six locations from the sub-humid prairie, and seven locations from the sub-boreal region. Not all grain samples were collected from every location due to non-availability of samples from that location. Grain samples were collected for barley (20 locations), Canada Western Amber Durum (CWAD) wheat (19 locations), Canada Western Red Spring (CWRS) wheat (22 locations), oats (16 locations), and rye (14 locations). For each grain type, 7500 kernels were selected to form the composite sample to represent all the growing locations. The composite sample included 300-550 randomly selected kernels from each location. This was done to simulate the practice in the industry where grains of the same grade from different locations are mixed together.

Image acquisition and feature extraction

For image acquisition, a 3-chip charge-coupled device (CCD) color camera (DXC-3000A, SONY) was used (Fig. 1). The camera had a zoom lens (VCL-1012 BY, SONY) of 10-120 mm focal length and a close-up lens set (72 mm, The Tiffen Company, Hauppauge, NY). The camera was connected to a personal computer (PC) (PIII 450 MHz) with a color frame grabbing board (Matrox Meteor-II multi-channel, Matrox Electronic Systems Ltd., Montreal, QC). To provide rigid stable support and easy vertical movement, the camera was mounted on a stand (M3, Bencher Inc., Chicago, IL). The camera was connected to a camera control unit (CCU-M3, SONY). A fluorescent tube with a 305 mm diameter 32-W circular lamp (FC12T9/CW, GE Lighting) with a rated voltage of 120 V was placed around and just below the surface level of the sample placement platform of the light chamber. A light diffuser, a semi-spherical steel bowl of 390 mm diameter, covered the light

bulb and the object plane so that the object plane was only exposed to the diffused light. The inner side of the bowl was painted white and smoked with magnesium oxide. The 72 mm close-up lens was used to achieve a spatial resolution of 0.064 mm/pixel in horizontal and vertical directions. The image acquisition, procedure, system calibration, details of the features, and the algorithm used to extract the features have been given elsewhere (Karunakaran et al. 2001, Visen 2002). A total of 230 features (51 morphological, 123 color, and 56 textural) was extracted from 7500 high resolution color images of each type of grain using the developed algorithm.

Classifiers

Neural networks were designed and implemented using the software package NeuroShell 2 (Ward Systems Group, Frederick, MD). NeuroShell Users Manual describes different types of neural networks, however, further details are available in several books (e.g., Bishop and Bishop 1996, Fausett 1994). Jayas et al. (2000) indicated that a BPN network is best suited and thus is the most popular choice for classification of agricultural produce. Visen et al. (2002) reported from preliminary studies that specialist networks result in very high (over 95%) classification accuracy when classifying cereal grains. Based on these results, network architectures were developed to determine classification accuracy for a large database of grain kernel images that were acquired from grain kernels obtained from several growing locations across the Canadian Prairies. A four-layer BPN was used for cereal grain classification. It consisted of up to 230 input nodes (number of input nodes equals number of input features used), 102 hidden nodes in two hidden layers, and five output nodes, one for each grain type. The number of hidden nodes was automatically calculated by the Neuroshell software using the equation:

$$\begin{aligned} \text{number of hidden nodes} \\ = (\text{number of input nodes} + \text{number of output nodes})/2 \\ + (\text{number of training patterns})^{0.5} \end{aligned}$$

The network used logistic scaling and activation functions at input and processing levels, respectively.

Training, testing, and validation of neural networks were performed using 37500 kernel images (7500 of each grain type). Training, testing, and validation were performed five times using different data sets. Each of the training and testing data sets consisted of 7500 images (1500 of each grain type) whereas the validation data set consisted of 22500 kernels (4500 of each grain type). The network was trained and tested for 1000 epochs and was then applied to the validation data set. The number of epochs was kept at 1000 to allow sufficient events before the training was stopped. The training was stopped if the minimum error value of the network remained unchanged for 20 training generations.

A specialist probabilistic network (SPNN) was developed which was a combination of five sub-networks (barley specialist network, CWAD wheat specialist network, CWRS wheat specialist network, oats specialist network, and rye specialist network). Each of the specialist sub-networks had up to 230 inputs (depending on number of features used) and two output categories. The number of hidden nodes was equal to the number of training patterns used. A sub-network specializing in a particular grain type, such as barley, was trained using data which consisted of two classes of output patterns - barley and

Table 1. Experimental parameters for the back propagation neural network classifier.

Experimental model	Number of input nodes	Number of hidden nodes	Training time (h)
Morphological	51	58	12
Color	123	76	64
Textural	56	58	15
All-features	230	102	75
Combined 60	60	60	28
Combined 30	30	52	10

‘the rest’. Each of the specialist sub-networks was trained to categorize an unknown object belonging to its class by assigning it a value between 0 and 1. A value close to 1 meant that the unknown object belonged to that class, barley for example, and a value close to 0 meant that the object belonged to any of the other classes (i.e., CWAD wheat, CWRS wheat, oats, or rye). The final outcome was determined by comparing the output of all the specialist sub-networks. The one having the highest value was used to assign the unknown object a grain type.

Training for SPNN using the genetic adaptive option (a feature of Neuroshell) was done in two parts. The first part trained the network with the data in the training set. The second part used calibration to test a whole range of smoothing factors, trying to optimize a combination that worked best on the test set with the network created in the first part. Completion of this step was treated as the elapsing of one generation. Training was completed when 20 generations elapsed without any improvement in the networks performance. At the end of training, the individual smoothing factors were used as a sensitivity analysis tool to determine the relative importance that input had towards the model. The network took less than a minute to train while the calibration procedure took up to 72 hours.

Classification models

A database of morphological, color, and textural features was created for each category (barley, CWAD wheat, CWRS wheat, oats, and rye) using 7500 kernels of each grain type, selected

Table 2. The top five morphological, color, and textural features based on their respective contributions towards classification accuracy for cereal grains in single kernel images while using a Back Propagation Neural Network classifier.

Rank	Features set		
	Morphological	Color	Textural
1	Perimeter	Red moment 1	Green GLCM mean
2	Mean radius	Red moment 2	Green GLCM cluster shade
3	Area	Green moment 3	Green GLRM runpercent
4	Boundary FD 2	Blue histogram range 1	Green GLCM variance
5	Minor axis length	Red moment 3	Blue GLCM mean

FD = Fourier Descriptor

GLCM = Gray Level Co-occurrence Matrix

GLRM = Gray Level Run Length Matrix

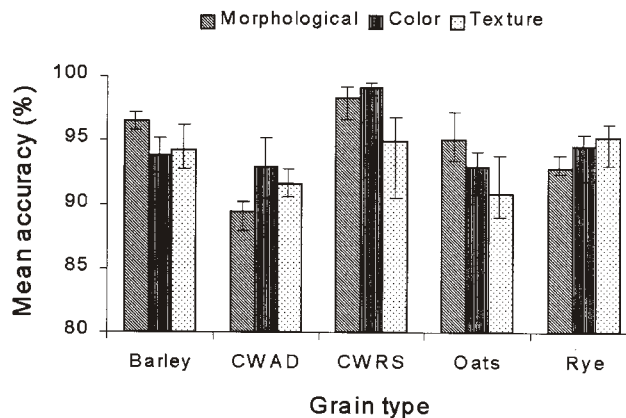


Fig. 2. Classification accuracies of the BPN classifier using morphological, color, and textural features as inputs. CWAD - Canada Western Amber Durum; CWRS - Canada Western Red Spring.

randomly from the different growing regions. The classification study was carried out using six different types of feature sets. The first three sets consisted of 51 morphological, 123 color, and 56 textural features, respectively. The fourth set consisted of all the morphological, color, and textural features combined, i.e., a total of 230 features. The fifth and sixth sets were subsets of the fourth set. They consisted of the top 10 and the top 20 morphological, color, and textural features combined, thus having a total of 30 and 60 features, respectively. The top 10 and top 20 features were determined from studies using the morphological, color, and textural feature models.

RESULTS

Classification accuracies for BPN

The experimental parameters for the BPN classifier are given in Table 1.

Morphological features model The top five features, ranked in order of their decreasing contribution to the classification process, are listed in Table 2. Perimeter, followed by mean radius and area, are the most important features when using a BPN. Size alone, however, is not sufficient. Shape features, such as Fourier descriptors, also rank high towards classification.

Except for CWAD wheat and rye, the mean classification accuracy of the morphological model for all the grain types was over 95% (Fig. 2). Low classification accuracies for CWAD wheat can be attributed to large variations in shape and size of the kernels. Most of the CWAD wheat kernels were misclassified as CWRS wheat kernels. This could be due to immature CWAD wheat grain kernels, which are closer to CWRS wheat grain kernels in shape and size. Majumdar and Jayas (2000a) reported misclassification due to close morphological resemblance between CWAD and CWRS wheats.

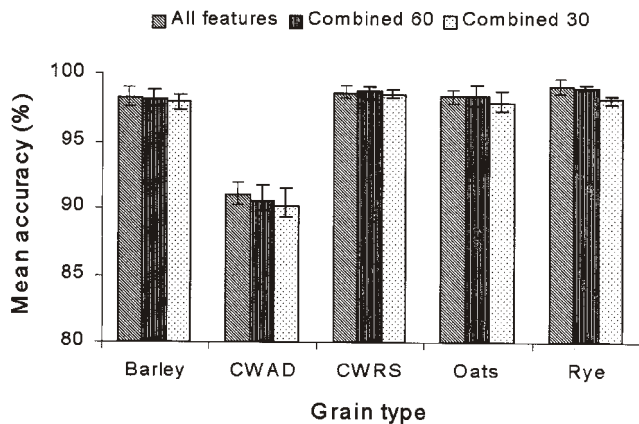


Fig. 3. Classification accuracies of the BPN classifier using the combined 30, the combined 60, and all features as inputs. CWAD - Canada Western Amber Durum; CWRS - Canada Western Red Spring.

Color features model The classification accuracies were high for all the grain types, with CWRS wheat getting nearly perfect results (Fig. 2). This model was more accurate than the morphological model for CWAD and CWRS wheat. The confusion matrices (not shown but are given in Visen 2002) revealed that barley was misclassified as CWAD wheat and oats, CWAD wheat was misclassified as barley and CWRS wheat, oats were misclassified as barley and rye, and rye was misclassified as CWAD wheat and oats. The top five features ranked according to their contributions are listed in Table 2. The histogram features contributed little to the classification process. Similar results were reported by Luo et al. (1999b). The red color band, including three of top five features, played an important role in classification.

Textural features model The classification accuracies obtained using textural features ranged from 90 to 95% (Fig. 2). Best results were for rye, closely followed by CWRS wheat and barley. Accuracies for CWAD wheat and oats were lower in comparison to the other grains. The CWAD wheat kernels were mainly misclassified as CWRS wheat kernels, whereas, oats were misclassified as barley. The top five features, ranked according to their contributions, are listed in Table 2. For textural analysis, the green band played an important role. Four of the top five textural features were from the green band. Co-occurrence matrix features were more important than run length matrix features.

Figure 2 shows a comparison of classification accuracies using morphological, color, and textural features with a BPN classifier. Classification accuracies for grains changed when using a different set of features. Barley and oats were best classified using morphological features, whereas CWAD wheat and CWRS wheat were best classified using color features. Texture alone did not produce good results, except for rye. Therefore, further trials were conducted by combining all the feature sets to increase the classification accuracy.

All-features model The classification accuracy for all the grain types, except for CWAD wheat, was over 98% (Fig. 3). Most of the CWAD wheat kernels were misclassified as CWRS wheat

kernels. This could be due to immature CWAD wheat kernels, which were closer to CWRS wheat grain kernels in appearance. Inclusion of grain samples from a large number of growing regions resulted in considerable overlap of similar looking grain types due to regional variability but testing of algorithms with such data is necessary for machine vision system to be used by the industry.

Combined 60 features model Except for CWAD wheat, the classification accuracy for all the grain types was over 98% (Fig. 3). The confusion matrix shows that in 8.3% of instances, CWAD wheat was misclassified as CWRS wheat. The classification accuracies did not change in comparison to the all-features model, even after eliminating a large number of features. This suggests that many of the features extracted were redundant and unnecessarily increased the complexity in the classifier without contributing towards the final output. This redundancy of features was also reported by Luo et al. (1999b).

Combined 30 features model Similar to combined 60 features model, the classification accuracy for all the grain types was over 97% (Fig. 3), except for CWAD wheat. More than 8% of CWAD wheat kernels were misclassified as CWRS wheat kernels. The classification accuracies slightly decreased for oats and rye as compared to the all-features and the combined 60 features model. This suggests that some of the useful features were eliminated when the features set was reduced from 60 to 30 features.

Figure 3 shows a comparison of classification accuracies using all-, combined 60-, and combined 30-features models with a BPN classifier. The analysis of variance, however, revealed that the classification accuracies obtained using different classifiers were not significantly different ($P < 0.05$) for barley, CWAD wheat, and CWRS wheat. Hence, the classifier using the combined 30 features set can be used for grain classification analysis using a BPN because it greatly reduces the computational time for feature extraction and classification processes without compromising the classification accuracies for oats and rye.

Classification accuracies for SPNN

Morphological features model The classification accuracies were as low as 82% for CWAD wheat and as high as 95% for CWRS wheat (Fig. 4). Table 3 lists the top five input features in descending order of their contribution for classification when using a SPNN classifier.

Color features model The classification accuracies were as low as 75% for oats and as high as 94% for CWRS wheat (Fig. 4). Table 4 lists the top five color features in descending order of their contribution to classification when using a SPNN classifier. The color histogram played an important role in classifying CWAD wheat and rye kernels, while the moment features were more important in classifying CWRS wheat and oat kernels. For barley, both histogram features and moments were in the top five features. Rye mainly used the red band, while CWAD wheat used data from the blue and the green band. CWRS wheat and oats also had characteristics defined by the red band, whereas barley used all the color bands in the top five features.

Textural features model The top five textural features in descending order of their contribution to classification when

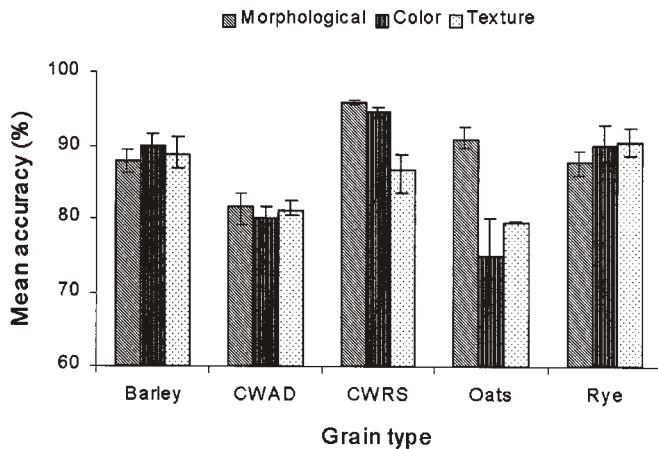


Fig. 4. Classification accuracies of the SPNN classifier using morphological, color, and textural features as inputs. CWAD - Canada Western Amber Durum; CWRS - Canada Western Red Spring.

using a SPNN classifier are given in Table 5. Of the top five features, the run length matrix features appear three times for barley and CWRS wheat. For CWAD wheat, oats, and rye, co-occurrence matrix features appear three times, respectively. Barley predominantly had features from the green band, whereas CWAD wheat and oats had three of the top five features from the blue band.

The classification accuracies of the BPN classifier were better than that obtained using the SPNN classifier. A comparison of classification accuracies using morphological, color, and textural features with a SPNN classifier is shown in

Table 3. The top five morphological features based on their respective contributions towards classification accuracy for cereal grains in single kernel images while using a Specialist Probabilistic Neural Network classifier.

Rank	Grain type				
	Barley	CWAD	CWRS	Oats	Rye
1	Boundary FD 6	Shape moment 4	Radial FD 4	Boundary FD 2	Minor axis length
2	Minimum radius	Maximum radius	Boundary FD 18	Boundary FD 14	Radial FD 16
3	Radial FD 2	Perimeter	Area	Perimeter	Major axis length
4	Minor axis length	Mean radius	Shape moment 4	Boundary FD 8	Radial FD 3
5	Boundary FD 16	Radial FD 5	Radial FD 2	Area	Boundary FD 3

FD = Fourier Descriptor

Table 4. The top five color features based on their respective contributions towards classification accuracy for cereal grains in single kernel images while using a Specialist Probabilistic Neural Network classifier.

Rank	Grain type				
	Barley	CWAD	CWRS	Oats	Rye
1	Red moment 1	Hue mean	Red moment 1	Red moment 2	Red histogram range 30
2	Blue histogram range 27	Blue histogram range 32	Red moment 2	Hue mean	Red histogram range 17
3	Red histogram range 25	Blue histogram range 1	Blue histogram range 10	Red moment 1	Red histogram range 25
4	Blue histogram range 19	Green histogram range 15	Green moment 2	Green moment 2	Red histogram range 15
5	Blue moment 4	Red histogram range 20	Hue mean	Intensity range	Green histogram range 30

Fig. 4. Classification accuracies for barley, CWAD wheat, and rye were in a close range irrespective of feature set used. The morphological set gave the best overall results for CWAD wheat, CWRS wheat, and oats.

All-features model The classification accuracies were over 94% for all the grain types except for CWAD wheat (Fig. 5), which was misclassified as CWRS wheat over 10% of the instances. The performance of the specialist network was better than the morphological, color, or textural models. The top five input features in descending order of their contribution for classification when using a SPNN classifier are given in Table 6. The top three features for barley were from the morphological set, making shape an important attribute to distinguish barley from other grain types. CWAD wheat classification made use of color and textural features from all color bands. No morphological feature appeared in the top five list. The top five feature list for CWRS wheat listed only one color and textural feature. For oats, all the features sets contribute substantially. However, the blue band appeared most of the time in the list. Rye made use of the textural and histogram features to separate itself from other grain types. The top five feature list included only one morphological feature.

The BPN classifier gave the best results for all grain types. Classification accuracies using BPN were over 97% except for CWAD wheat, for which all the classifiers showed a drop in performance (Fig. 3). The SPNN classifier showed a trend similar to the BPN, however, the accuracies remained slightly lower (Fig. 5).

Combined 60 features model The classification accuracies were over 93% for all the grain types except for CWAD wheat (Fig. 5), which, like other classifiers, got misclassified as

Table 5. The top five textural features based on their respective contributions towards classification accuracy for cereal grains in single kernel images while using a Specialist Probabilistic Neural Network classifier.

Rank	Grain type				
	Barley	CWAD	CWRS	Oats	Rye
1	Green GLRM long run	Blue GLCM homogeneity	Gray GLRM entropy	Blue GLCM variance	Blue GLCM mean
2	Blue GLRM long run	Blue GLRM short run	Gray GLRM run length non-uniformity	Green GLRM short run	Red GLCM mean
3	Green GLCM mean	Blue GLCM variance	Green GLCM correlation	Red GLRM short run	Green GLRM runpercent
4	Green GLRM short run	Red GLRM entropy	Red GLCM correlation	Blue GLCM mean	Green GLRM long run
5	Gray GLRM runpercent	Green GLCM variance	Green GLRM long run	Blue GLCM cluster shade	Blue GLCM variance

GLCM = Gray Level Co-occurrence Matrix
 GLRM = Gray Level Run Length Matrix

Table 6. The top five features from all-features set based on their respective contributions towards classification accuracy for cereal grains in single kernel images while using a Specialist Probabilistic Neural Network classifier.

Rank	Grain type				
	Barley	CWAD	CWRS	Oats	Rye
1	Radial FD 2	Saturation mean	Radial FD 2	Gray GLRM short run	Radial FD 6
2	Minor axis length	Hue mean	Hue mean	Boundary FD 2	Gray GLRM short run
3	Boundary FD 16	Red histogram range 24	Major axis length	Blue histogram range 14	Green GLRM long run
4	Blue histogram range 6	Blue histogram range 6	Green GLCM mean	Red histogram range 24	Green histogram range 21
5	Green GLCM homogeneity	Gray GLCM inertia	Boundary FD 20	Blue histogram range 11	Blue histogram range 14

FD = Fourier Descriptor
 GLCM = Gray Level Co-occurrence Matrix
 GLRM = Gray Level Run Length Matrix

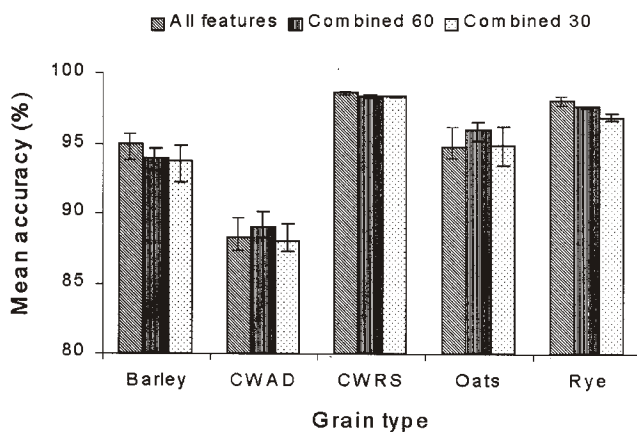


Fig. 5. Classification accuracies of the SPNN classifier using the combined 30, the combined 60, and all features sets as inputs. CWAD - Canada Western Amber Durum; CWRS - Canada Western Red Spring.

CWRS wheat for 9.8% of the kernels in the production set. The performance of the specialist network did not decrease when compared to the all-features model, even though the number of features decreased from 230 to 60. Thus, it was concluded that there were a lot of redundant features in the all-features set.

The BPN classifier gave best results for all the grain types. Classification accuracies using BPN were over 97% except for CWAD wheat, which showed a drop with all the classifiers (Fig. 2). The SPNN classifier showed a trend similar to the BPN. However, the accuracies remained slightly lower in comparison to the BPN (Fig. 4).

Combined 30 features model The classification accuracies were over 93% for all the grain types except for CWAD wheat (Fig. 5). The BPN outperformed the SPNN classifier. It gave the highest classification accuracies for all grain types except for CWAD wheat, which was second highest. The SPNN had the same results as the BPN for CWRS wheat.

The classification accuracies obtained for the combined 30-, the combined 60-, and all-features sets using a SPNN classifier are shown in Fig. 5. Further analysis of results using analysis of variance showed that the classification accuracies were not statistically different. Therefore, the combined 30 features set is recommended for grain classification when using a SPNN classifier.

Table 7. Classification accuracies of CWAD and CWRS wheat kernels obtained using a CCSN for grain kernels that were classified as CWAD or CWRS wheat kernels by the combined 60 features set based SPNN.

	Classification accuracy for three trials (%)			
	1	2	3	Mean
CWAD	92.0	92.2	92.1	92.1
CWRS	98.1	98.3	98.6	98.3

DISCUSSION

Analysis of the BPN and SPNN classifiers showed that for all the feature models, CWAD wheat was often misclassified as CWRS wheat. To overcome this situation, a CWAD-CWRS specialist network (CCSN) was developed and tested in conjunction with the SPNN network using the combined 60 features. The CCSN had an architecture similar to a specialist sub-network except that it used a total of the best 30 features common to the CWAD-combined-60 specialist network and the CWRS-combined-60 specialist network. Hence, the network consisted of 30 input, 7500 hidden, and two output nodes. The network was trained using a data set that consisted of just the CWAD and CWRS wheat kernels. Using a CCSN, a modified SPNN was developed whose function is described as follows:

1. In the first step, an unknown grain kernel was presented to the SPNN using the combined 60 features set.
2. If the grain kernel was classified (or misclassified) as barley, oats, or rye, the classification process stopped and the unknown kernel was assigned the class determined by the network.
3. If the grain kernel was classified as CWAD or CWRS wheat, its top 30 features (as determined above) were presented to the CCSN. The output of the CCSN was assigned as the class of the unknown grain kernel. The classification accuracies obtained from the modified SPNN are shown in Table 7.

The results indicate that the classification accuracies improved significantly ($P < 0.05$ for paired t-test) for CWAD wheat. Initially, 9.75% of CWAD kernels had been misclassified as CWRS wheat. There was no significant change in classification results for CWRS wheat because not too many CWRS wheat kernels were misclassified as CWAD wheat.

The classification accuracies using SPNN were not as high (over 95%) as previously reported by Visen et al. (2002). This could be attributed to the difference in percentages of training set data with respect to overall data. In the preliminary study, the training was done on 80% of the total data and the trained network was applied on all the data, including training data. This resulted in over-learning by the network for most of the training data. However, in the current study, training was done on 25% of the total data and then tested on the “never-before-seen” 75% of the data. The classification accuracies using the BPN in both the studies were comparable. Such characteristic performance of BPN and SPNN classifiers could be attributed

to the fact that BPN had better ability to generalize data, whereas SPNN tended to memorize and over-fit the data.

CONCLUSION

A computer program was written to extract 230 features (51 morphological, 123 color, and 56 textural) that could be used in different combinations to attain the best classification results. Two different neural network architectures were evaluated and their classification accuracies were compared using various feature models. Based on the preliminary results, the classifiers were modified by training them with optimized feature sets to improve the classification accuracies. Mean classification accuracies of 96.9, 95.0, and 95.5% were obtained when the combined 60 features were used for grain classification using BPN, SPNN, and the modified SPNN classifiers, respectively. Using the combined 30 features, classification accuracies of 96.4 and 94.3% were obtained using BPN and SPNN classifiers, respectively. It was concluded that all (morphological, color, and textural) features played an important role in the grain classification process. An excessive number of these features could have a detrimental effect on the classifier by inducing redundancies and increasing computational time of the classifiers.

A novel concept of a specialist neural network was introduced in this study for the purpose of grain classification. These networks specialized in differentiating a particular grain type from another or all of the grain types. The downside of these networks was that they were complex and require more memory and computational power. They, however, serve as a very effective tool for post-processing of another network's output to improve the overall classification accuracy.

ACKNOWLEDGMENTS

We thank the Natural Sciences and Engineering Research Council of Canada, University of Manitoba Graduate Fellowship Committee, and Canada Research Chairs Program for partial funding of this study. We also thank L. Wang and C. Karunakaran for algorithm development.

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