A machine vision system for grading lentils

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Shahin, M.A. and Symons, S.J. 2001. **A machine vision system for grading lentils**. Canadian Biosystems Engineering/Le génie des biosystèmes au Canada 43:7.7-7.14. Color and appearance of lentils are important grading factors. A machine vision system for color grading of lentils was developed using a flatbed scanner as the image-gathering device. Grain samples belonging to different grades of large green lentils were scanned and analyzed over a two-crop season period. Image color, color distribution, and textural features were found to be good indicators of lentil grade. Linear discriminant analysis, k-nearest neighbors, and neural network based classifiers performed equally well in predicting sample grade. An online classification system was developed with a neural classifier that achieved an overall accuracy (agreement with the grain inspectors) of more than 90%. **Keywords**: lentils, grading, inspection, machine vision, color, image analysis, image classification, flatbed scanner.

La couleur et l'apparence sont deux facteurs importants de classement des lentilles. Un système de vision artificielle, pour lequel l'acquisition d'images se faisait à l'aide d'un lecteur optique plat, fut développé pour classer les lentilles selon la couleur. Au cours d'une saison de deux récoltes, des échantillons de lentilles vertes de catégories différentes furent examinés. Il semble que la couleur de l'image, la distribution des couleurs et les paramètres texturaux soient de bons indicateurs de la catégorie des lentilles. Les facteurs de classement dérivés d'une analyse discriminante linéaire, de la méthode du plus proche voisin et d'un réseau de neurones ont prédit de manière équivalente la catégorie des échantillons de lentilles. Un système de classement en temps réel fut développé avec un facteur de classement neuronal dont la précision globale (accord avec le travail des inspecteurs des grains) dépassait 90%. **Mots clés**: lentilles, classement, inspection, vision artificielle, couleur, analyse des images, classification d'images, lecteur optique plat.

INTRODUCTION

Lentils have emerged as a specialty crop in the prairies due to their high value. Consequently, the area under lentil production has increased many fold over the last few years. Canada now exports about 2.7 million tonnes of lentils annually (Personal communication: Gordon Bacon, President, Pulse Canada, Winnipeg, MB).Visual appeal directly influences consumer acceptance and hence value of the lentil product. The main visual factor is the color of the grain, which is directly related to its market value. Errors in color assessment can lead to incorrect grade assignments, especially close to the grade boundaries, causing a further perception that visual grading is incorrect. As grade is related to value, growers may not be paid what their crop is actually worth.

At present, lentils are graded through visual inspection by trained inspectors according to the guidelines set by the Canadian Grain Commission (Anonymous 1998). Human visual inspection, by nature, is a highly subjective process due to complexity involved in human color perception. Experienced inspectors are usually very consistent in their own assessment of grade. Disagreements among inspectors, however, occur because of vague boundary cut-offs between grades and different personal experiences and color acuity. To increase consistency at grade boundaries, several inspectors often concur to reach a consensus for such samples. This slows down the inspection process, as there is no definitive description of the acceptable color ranges in each grade. The measurement of color using a machine vision system offers a potential solution to placing color evaluation on an objective basis.

Machine vision is a well-established inspection tool in the automotive industry. Its use in the field of agriculture has been the area of active research in the last decade. Several systems have been reported in the literature for inspecting a variety of products ranging from fruits (Kodaira et al. 1991; Singh et al. 1993; Al-Janobi and Kranzler 1994; Shahin and Tollner 1998) and vegetables (Marchant et al. 1990; Shearer and Payne 1990; Shahin et al. 1999) to grains (Hehn and Sokhansanj 1990; Zayas et al. 1990; Reid et al. 1991), eggs (Patel et al. 1996), and fish (Strachan 1993). For grading or sorting lentils, two systems have been reported: one developed at the University of Saskatchewan (Winter 1997) and the other developed by a seed sorting company in Rocanville, Saskatchewan (Personal communication: Lavern Affleck, Owner, Agrivision Processing Co., Rocanville, SK). Both of these systems, however, generally rely upon expensive mechanical hardware or difficult to maintain color camera technology, which limits their affordability, portability, consistency, and reproducibility between systems and the ability to handle small samples. A robust, cost effective, and portable system capable of predicting color and grade in real-world applications would be very useful to both the lentil growers and inspectors. Traditionally, in a machine vision system, images for analysis are gathered using a video camera. While this is effective, the information contained within the image can be influenced by changes in the camera configuration and by slight changes to the way in which the sample is illuminated. This is a complex problem for color imaging, where any slight change in the image gathering system can cause dramatic changes in the color information contained in the image. Video camera input devices also are expensive to purchase and maintain. An imaging device that is less sensitive to ambient lighting conditions as well as less costly than a video camera would lead to a robust and cost effective grading system.

Flatbed (document) scanners are image gathering devices that incorporate a fixed relationship between the illuminant source (lamp) and the solid state sensors of the scanning head. Due to their increasing popularity, the cost of these devices is dropping rapidly. These characteristics may turn the flatbed scanners into the image acquisition system of choice.

Table 1. **Number of samples for different color grades scanned each year.**

Color	Description	Grade	Number of samples	
			1998	1999
GNCLR	Good natural color	1	114	587
RGCLR	Reasonably good color	2	146	78
F2PCLR	Fair-to-poor color	3	70	24
Total samples			330	689

Preliminary investigations showed that a flatbed scanner could be used as an alternative imaging device (Shahin and Symons 1999).

The overall objective of this research was to develop a robust, cost effective and practical machine vision system for color grading of lentils using a flatbed scanner. Specific objectives were to:

1. Verify the suitability of a flatbed scanner as a quantitative imaging device for detecting color variations associated with color grades of large green lentils.
2. Extract image features indicative of the color grade of large green lentils and evaluate selected image features using statistical and neural network classifiers.
3. Develop an online classification system for grading lentil samples into their appropriate color grades based on selected image features.

MATERIALS and METHODS

Samples of large green seeded (Laird) lentils were collected over two years from the 1998 and 1999 crops. Images of these samples were acquired using a flatbed scanner. Data from the 1998 crop were utilized for development and validation of the classification (grading) system. Data from the 1999 crop were used for verification of the system performance.

Lentil samples

For the crop year 1998, 260 samples were received from the Industry Service Division, Canadian Grain Commission (CGC) offices in Saskatchewan. These samples were from storage and at least 120 days old. When a grade did not appear to match the visual appearance of the sample, senior inspectors in Winnipeg re-inspected the samples and assigned a grade. Samples were about 800 g in size. About 70 samples were also obtained from the 1998 New Crop Survey carried out by the Grain Research Laboratory (GRL). These samples represented individual producer samples. Again, the CGC Industry Services Division graded these samples. A total of 330 samples of Laird lentils received from 1998 crop were scanned.

For the 1999 crop, 689 samples of Laird lentils were received. These samples were scanned immediately after visual inspection at the Industry Service Division, CGC office in Saskatoon, Saskatchewan. Image features extracted from these samples were exclusively used for performance verification of the system developed with data from the 1998 crop. Table 1 shows the number of samples representing different color grades for each year.

According to CGC guidelines, lentils are categorized into four color-classes: ‘Good Natural Color (GNCLR)’, ‘Reasonably Good Color (RGCLR)’, ‘Fair Color (FRCLR)’ and ‘Poor Color (PRCLR)’. Due to fewer number of samples representing FRCLR and PRCLR color grades available during the 1998-99 period, these two color grades were collectively graded as “Fair-to-Poor Color” (F2PCLR; grade 3).

Hardware and software

The vision system’s hardware consisted of a flatbed scanner (ScanMaker III, Microtek, Denver, CO), a personal computer with Pentium CPU (200 MHz), scanner interface card, and a color monitor for online image display. The software consisted of a TWAIN-compliant scanner controller (ScanWizard version 2.52, Microtek, Denver, CO) for image acquisition and an image processing software (KS-400 version 3.0, Carl Zeiss Vision, Germany) for image analyses. The imaging software offered a multitude of built-in measurement parameters from which to choose.

Image acquisition

Several different approaches of presenting the sample to the scanner bed were evaluated. The method selected incorporated a sample holder machined in a clear plastic. The sample holder (200 mm by 200 mm by 20mm) covered the width of the scanner bed. A non-reflecting black sheet covered the remainder of the scanner bed. For imaging, a thoroughly mixed sample was poured into the middle of the sample holder. A gentle downward push at the top of the seed heap caused the grains to cover the entire bottom surface of the sample holder with most grains laying flat. Images were captured in a variety of scenarios including room lighting, room lights off and the exclusion of room light from the scanner. Limiting or removing the effects of room lighting had no effect on the image features. The image capture system was therefore used on a bench with ambient room light. This contrasted dramatically with the configuration that would have been required if a color camera had been selected. With a camera, ambient illumination is very critical for reproducible imaging.

For each of the samples, a 512 by 512 pixel image was captured at 100 dpi (dots per inch) from the center of the field of view for later analyses. The size of the window and spatial resolution were determined on the basis of preliminary experiments as discussed later under results. A macro written in the imaging software controlled the scanner through a TWAIN interface.

Image analysis and feature selection

In grading lentils, color is evaluated after the removal of stained, damaged, and peeled or split seeds. Therefore, image areas corresponding to damaged and split seeds were segmented before measuring image features indicative of the color grade. Damaged lentils could be distinctly green or dark brown in color that would stand out in the red-green-blue (RGB) color domain. Due to the wide range of color characteristics of damaged lentils, histogram-based dynamic threshold in the RGB domain was used to segregate highly contrasting seeds in the image. Morphological opening was used to ‘clean up’ the binary image. Split seeds (yellow) were segregated using fixed threshold values in the hue-light-saturation (HLS) domain. Image areas corresponding to damaged and split seeds were subtracted from the original image before measuring the features of interest.

Color and uniformity of color were considered the key determinants of the color grade. Hence, the basic statistics (mean, minimum, maximum, and variance) for the RGB and HLS channels were recorded as the measures of the base color of the sample. Color histograms (R and G channels) and image texture parameters (Haralick et al. 1973) were measured as the measures of color uniformity and overall appearance of the sample. Also, image areas proportional to green and pink seeds were measured to represent good and oxidized seeds in the sample, respectively. Approximately 100 image features were extracted from each sample image based on experience and common sense.

For the 1998 crop year, features extracted from images of all 330 samples were stored in a data set along with the respective visual color grades assigned by CGC inspectors. The entire data set was used for selecting significant features based on their contribution towards the desired classification. The SAS procedure STEPDISC was used for feature selection (SAS 1997). The Wilk's lambda and the average-squared-canonical-correlation (ASCC) were used as the criteria of significance. The data set was then reduced to contain only 25 features (picked by the selection procedure) along with the assigned color grades. This reduced data set from the 1998 crop was subdivided into a training set and a test set through random assignments. The training set (consisting of 60 samples of GNCLR, 70 samples of RGCLR and 33 samples of F2PCLR) was used to develop the color models (classifiers). Whereas, the test set (consisting of 54 samples of GNCLR, 76 samples of RGCLR, and 37 samples of F2PCLR) was used to evaluate the performance of the classifier models. The data from the 1999 crop samples was used for cross validation of the classifier model developed with the data from the 1998 crop samples.

Classification

The selected image features were evaluated for their ability to predict lentil grade by color. Three different color classifiers were built (trained) using the training set. The linear discriminant analysis (LDA) and non-parametric (NPAR) classifiers were trained using the SAS procedure DISCRIM (SAS 1997) while a multilayer neural network (MNN) was trained by using a dedicated neural network software package (Propagator, ARD, Columbia, MD).

For the LDA model, equal prior probability for all the color grades was assumed to avoid classification bias. The NPAR models were developed using k-nearest neighbors where k was varied from 3 to 10. For the MNN models, 3-layered, single-output fully connected architecture was used. The input layer consisted of 25 neurons (equal to the number of input variables) with a linear transfer function. Five neurons were used in the hidden layer based on trial-and-error. The sigmoid (logistic) transfer function was used for the hidden and output layers. The 25-5-1 neural network was trained using the error-back-propagation method with the patterns in the training set presented in a random fashion. The weights were adjusted using the generalized delta rule and training was stopped when the weights were not updated for 1000 epochs. Using a learning rate of 0.3 and momentum of 0.5, it took approximately 2 minutes to train on a Pentiun II processor.

After training, all three classifiers were evaluated using the test data set that was independent of the training data. In each case, the classifier's outcome was compared with the known visual grade, and performance of the classifier was judged based on accuracy of prediction. The best of the three classifiers was picked for the online system.

Online grading system

The classifier with the highest correct classification on the test set was implemented by writing a macro-language subroutine within the imaging software. This program scanned the sample, measured 25 image features as determined by the selection procedure, assigned a color grade, and displayed the results as an integrated application. The classification accuracy of this online system was evaluated by scanning 689 samples drawn from the 1999 crop. Also, the average time required to grade individual samples was determined from ten time-measurements.

RESULTS and DISCUSSION

Scanner evaluation

Images in Fig. 1 (a-c) represent color scans of characteristic lentil samples of different grades. The visual color and appearance of these images are distinctly different from one another, however, in reality samples have appearances that span the continuum. Seeds with different colors – green, pink, yellow, and brown – are obviously identifiable. This visually confirms the ability of the flatbed scanner to detect color variations among lentil samples of different grades.

The scanner's consistency and repeatability was tested by comparing values of individual color channels measured from images of the same lentil sample acquired over a number of days. The sample poured at day one was kept undisturbed throughout the length of the experiment to ensure that the images compared were consistent. Standard color charts were not used because relatively small color drifts within the narrow color band of lentils might not be clearly seen due to the broad color band of the color charts. For a fifteen-day period, the values of the R, G, and B components were consistent (Fig. 2). Any drifts in values were within acceptable instrument variation and less than the drift recorded for color camera systems in other projects in the same laboratory. This confirms that the flatbed scanner being used generates repeatable color information and may be a good alternative to video cameras for quantitative imaging.

The time taken to scan an image is directly related to both size and spatial resolution within the image. The objective for rapid image processing is to gather sufficient information to allow the classifier to produce accurate predictions. Excessive amounts of information that do not improve the classifier slow the imaging process due to data volume. Size and resolution of the image control data volume that in turn affects the processing time.

When the color information contained in images of different size (512 x 512, 700 x 700, and 780 x 780 pixels) was compared at a single resolution of 100 dpi, image size was

(a) Good natural color

(b) Reasonably good color

(c) Fair-to-poor color

Fig. 1. Images of lentil samples with different color grades: (a) grade 1, (b) grade 2, and (c) grade3.

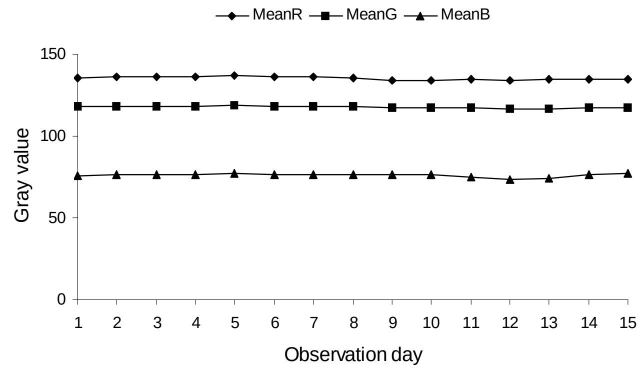


Fig. 2. Scanner repeatability: variation in color features over time.

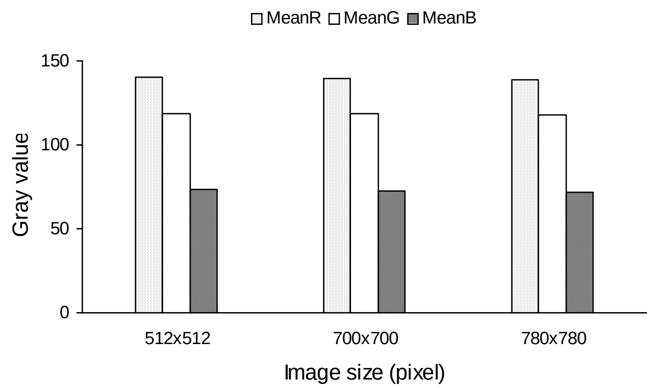


Fig. 3. Effect of image size on image color features.

found not to affect the color information (Fig. 3). The smallest size of 512 x 512 pixels image was selected for further evaluation. Images smaller than 512 x 512 pixels were not considered suitable because the sample area captured by smaller images would not be representative of the sample. Also, the number of pixels per seed for smaller seeded varieties would not provide sufficient accuracy for planned size measurements.

Similarly, when color information in 512 x 512 pixel images was compared at resolutions of 100, 200, and 300 dpi, no significant difference between image resolution was found (Fig. 4). For the fastest image processing the lowest resolution of 100 dpi was selected. Scanning at a resolution lower than 100 dpi was not supported with the scanner used. More importantly, imaging at lower than 100 dpi might not capture stain damage where a part of the seed is discolored.

Image analysis and feature selection

In visual color grading of lentils, damaged and peeled seeds are physically removed out of samples prior to color assessment of the remaining sample. This segregation was accomplished through image processing rather than physical separation prior to color analysis (Fig. 5). Histogram based color segmentation followed by morphological opening successfully segregated the damaged seeds. Both the dark tan and distinctly green seeds were identified in one operation that would otherwise require at least two threshold operations. However, partially occluded

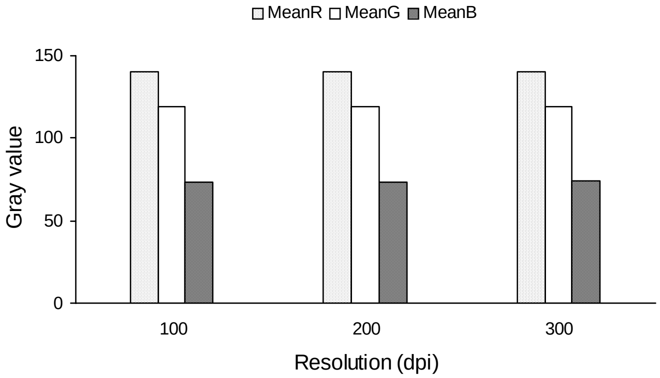
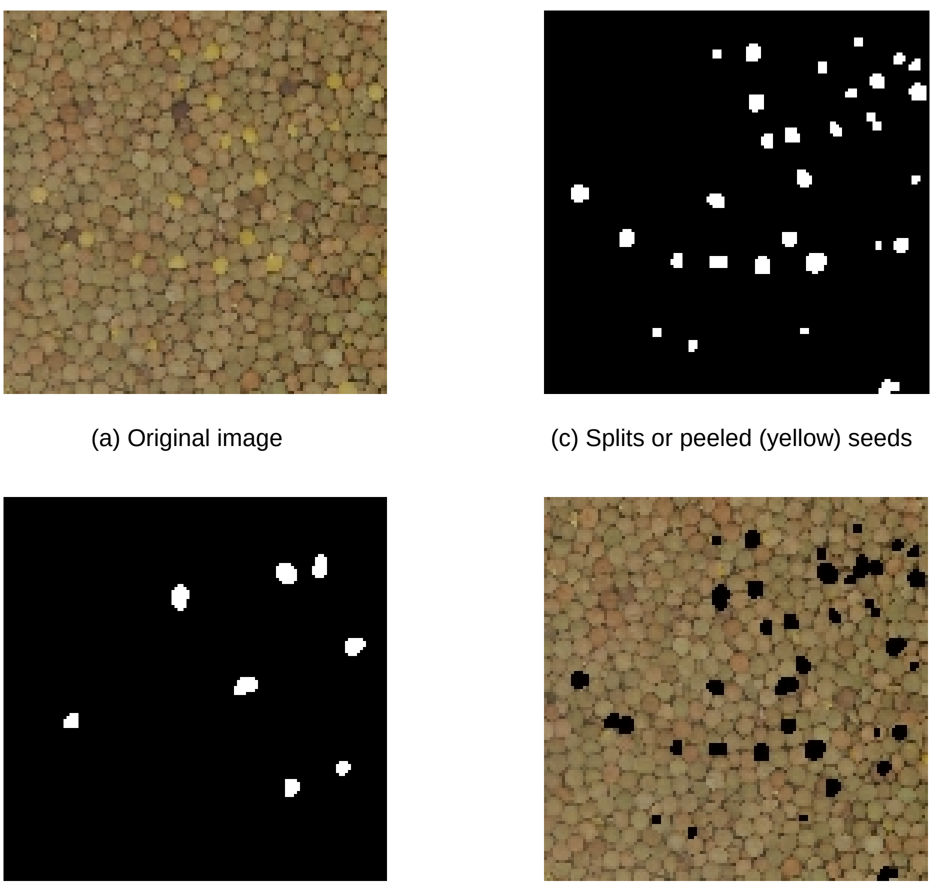


Fig. 4. Effect of image resolution on image color features.

seeds (green or tan) in some images were also picked as damaged seeds due to shadowing effect. It was not possible to avoid these darker areas from being recognized as damage. Even the fixed thresholds failed to discriminate among damaged and occluded seeds. Removal of these darker areas from the image may be considered positive as far as color assessment is concerned, however, it could affect the overall grade based on excessive damage. A little care in pouring the sample in the sample holder can minimize “voids” in the image. In comparison, difference can be found between inspectors in their assessment of these characteristics. Overall, there was a very good agreement between visual and machine vision detection. The histogram based approach was chosen since there is no explicit definition of desired color. This varies according to variety and seed size. The apparent uniformity in appearance is, however, critical and the ‘non-desirable’ seeds are relative to the sound color base of each sample.

Segmentation using fixed threshold values in the HLS domain was successful in segregating splits or peeled seeds. Approximately all of the peeled seeds were segregated – only the occluded peeled seeds were missed; but, some discolored seeds (seeds with a yellowish tint or yellow-green to light brown color in some samples) were also picked as yellow ones due to overlapping spectral boundaries. Overall, the segmentation process removed more than 95% of the damaged and peeled seeds as compared to the CGC inspectors. However, removal of discolored seeds as peeled may lead to misclassification of some samples of lower quality where these factors predominate. Separation of damaged and peeled seeds was a big step toward true color assessment of samples. This would allow for upgrading of samples having good color downgraded due to other factors such as damaged, diseased, or peeled seeds.

The imaging software in which the application was developed has a multitude of measurement parameters. For each new set of measurement features, a statistical discriminant model was developed and the predicted outcomes of the training data evaluated. The features considered included proportional areas of the segmented image corresponding to green and oxidized seeds, overall image color (RGB and hue statistics), color histograms (reduced to 32 gray levels), and texture features (Haralick coefficients). The selection procedure found 25 image features (out of 100 tested) as significant contributors towards the desired classification based on decrease in the Wilk’s lambda and increase in the ASCC. Selection and ranking of these features would depend on a number of factors: 1) make and model of the scanner used, 2) scanner settings, 3) imaging library used for image analysis, 4) who graded the samples, and so on. While the selected features may vary depending upon the image gathering and image analysis circumstances, the procedure outlined here provides sufficient details for any one familiar with image analysis and statistical techniques to select appropriate features for a given application.



(a) Original image

(c) Splits or peeled (yellow) seeds

(b) Damaged (dark brown) seeds

(d) Original minus splits and damaged

Fig. 5. Separation of damaged and peeled seeds by color segmentation.

Table 2. Classification results using the Linear Discriminant Analysis (LDA) model on the test data set (number of samples predicted into color).

	Into color			Total	Accuracy	False alarm
From color	GNCLR	RGCLR	F2PCLR	(actual)	(%)	(%)
GNCLR	50	4	0	54	93	14
RGCLR	8	68	0	76	89	9
F2PCLR	0	3	34	37	92	0
Total (P)	58	75	34	167	91	9

GNCLR - Good natural color
RGCLR - Reasonably good color
F2PCLR - Fair-to-poor color
Actual - By visual inspection
P - Predicted

Table 3. Classification results using the Non-Parametric Analysis (NPAR) model on the test data set (number of samples predicted into color).

	Into color			Total	Accuracy	False alarm
From color	GNCLR	RGCLR	F2PCLR	(actual)	(%)	(%)
GNCLR	52	2	0	54	96	22
RGCLR	15	61	0	76	80	8
F2PCLR	0	3	34	37	92	0
Total (P)	67	66	34	167	88	12

GNCLR - Good natural color
RGCLR - Reasonably good color
F2PCLR - Fair-to-poor color
Actual - By visual inspection
P - Predicted

Table 4. Classification results using the Multilayered Neural Network (MNN) model on the test data set (percent classified into color).

	Into color			Total	Accuracy	False alarm
From color	GNCLR	RGCLR	F2PCLR	(actual)	(%)	(%)
GNCLR	51	3	0	54	94	14
RGCLR	8	65	3	76	86	7
F2PCLR	0	2	35	37	95	8
Total (P)	59	70	38	167	90	10

GNCLR - Good natural color
RGCLR - Reasonably good color
F2PCLR - Fair-to-poor color
Actual - By visual inspection
P - Predicted

Classification

Three different kinds of classification model (LDA, NPAR, and MNN) were developed and tested for predicting color grades of lentils. The model that performed best was picked for developing the online grading system.

The best results for the LDA classifier are given in Table 2. The LDA classifier correctly classified 152 out of 167 samples in the test set. Hence, an overall prediction accuracy of 91% was achieved on the test set (93% on the training set). In every case of misclassification, the color grade predicted was consistently biased towards one of the adjacent color grades. Overall, 2.4% of the samples (4 out of 167) were downgraded while 6.6% of the samples (11 out of 167) were upgraded. Grade-by-grade accuracy of 93, 89, and 92% was observed for GNCLR, RGCLR, and F2PCLR, respectively. Purity of the predicted classes was determined by the false alarm. For example, 8 of the 58 samples (14% false alarms) predicted as GNCLR were actually RGCLR. For RGCLR, 9% of the samples were falsely classified into this color class. When comparing the classification models developed and their respective accuracy, it has to be considered in comparison to the reference method. While the reference method is the best available and represents accepted trading characteristics, it is subject to error. The visual reference method through various legislated appeal processes typically needs to re-inspect a substantial number of samples every crop season. During re-inspection, the grades on a number of samples may change. Data on the appealed samples were not accessible for comparison with the machine vision system.

Discriminant models can also be developed using non-parametric (NPAR) statistics. Non-parametric statistics offer a method to evaluate data when the contributions of the measured features to the discriminant model are not linear. For the NPAR classifier, overall accuracy of 88% was found on the test set (96% on the training set) (Table 3). This classifier gave no advantages over the LDA classifier. Overall, 1.2% of the samples (2 out of 167) were downgraded while 10.8% of the samples (18 out of 167) were upgraded. Grade-by-grade accuracy of 96, 80, and 92% was observed for GNCLR, RGCLR and F2PCLR, respectively. False alarms for GNCLR and RGCLR were 22 and 8%, respectively.

Neural networks offer a fast alternative to discriminant models. They can be developed using both linear and non-linear characteristics within a single model. The multilayer neural

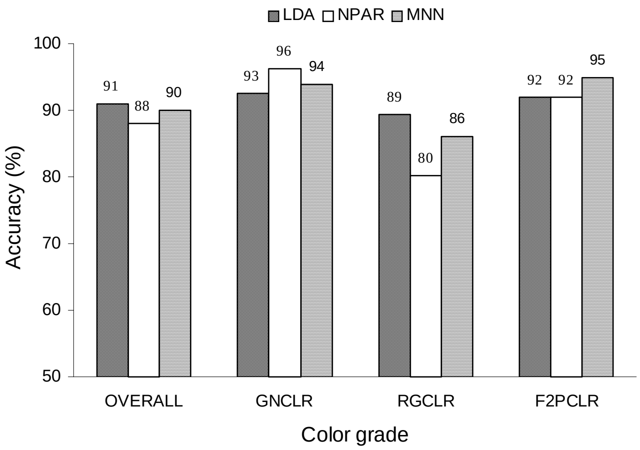


Fig. 6. Comparison of classification results using linear discriminant analysis (LDA), non-parametric (NPAR), and neural network (MNN) classifier models.

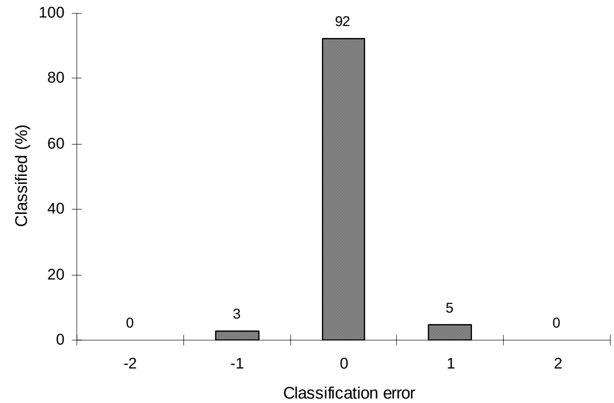


Fig. 7. Performance of the online grading system for 1999 crop. Errors of -1, 0, 1 indicate downgrades, correct classification, and upgrades, respectively.

network (MNN) classifier achieved an overall accuracy of 90% on the test set and 94% on the training set (Table 4). Overall, 3.6% of the samples (6 out of 167) were downgraded while 6% of the samples (10 out of 167) were upgraded. Grade-by-grade accuracy of 94, 86, and 95% was observed for GNCLR, RGCLR, and F2PCLR, respectively. False alarms for GNCLR, RGCLR, and F2PCLR were 14, 7, and 8%, respectively.

An overall comparison of the three modeling approaches (Fig. 6) shows that all three models have similar classification accuracy. However, when the three approaches are compared on a grade by grade basis, LDA and MNN models have slightly better overall performance than the NPAR classifier that is biased toward GNCLR. For the NPAR classifier, 15 out of 67 samples predicted as GNCLR were actually RGCLR (22% false alarm as compared to 14% for LDA and MNN). Ability to accurately predict GNCLR (grade 1) is very important from the growers' standpoint as misclassification of grade 1 samples will lead to downgrading of the lot, lowering the value, and causing loss to growers, whereas, accuracy of prediction for the other grades is important for the buyers. The NPAR classifier (96%) predicts grade 1 lentils slightly more accurately than the LDA (93%) and MNN (94%) models, but the differences are not significant. For lentils of reasonably good color, however, both the LDA (89%) and MNN (86%) classifiers perform significantly better than the NPAR (80%) classifier. Based on these observations, the LDA and MNN models were considered slightly better options than the NPAR model. However, the MNN classifier was selected for the online system because it is much simpler to implement and relies far less on the statistical properties of the input data than the statistical models.

Online grading system

To facilitate 'real-time' classification of samples a 3-layered MNN with 25 input nodes, 5 hidden nodes, and a single output node (the same classifier that was used for 1998 data) was implemented within the imaging software. This online system, when tested on 30 samples of all three grades randomly selected from the 1998 crop, exhibited a repeatability of approximately 96%. For samples with GNCLR, repeatability approached 100%. The system repeatability was determined by re-pouring and re-grading each of these samples 10 times.

The MNN-based system developed with 1998 data was also tested on 689 samples from the 1999 crop. For the second year testing (verification of 1998 model with the 1999 data), the system achieved an overall accuracy of 92% with the downgrades and upgrades limited to 3 and 5%, respectively (Fig. 7). For the two extreme grades (GNCLR and F2PCLR), the system output matched the visual grade very well (accuracy over 96% for these two color grades), however, accuracy for RGCLR was low (60%) (Table 5). Misclassification usually occurred for samples on the grade boundary. The system as such favors the growers, as the percentage of the upgrades is a little higher than the downgrades. Low accuracy for RGCLR samples may be due to inaccuracy in

Table 5. Classification results for the online grading system with MNN classifier on the 1999 crop (number of samples predicted into color).

	Into color			Total (actual)	Accuracy (%)	False alarm (%)
From color	GNCLR	RGCLR	F2PCLR			
GNCLR	567	20	0	587	97	5
RGCLR	31	47	0	78	60	32
F2PCLR	0	2	22	24	92	0
Total (P)	598	69	22	689	92	8

GNCLR - Good natural color
RGCLR - Reasonably good color
F2PCLR - Fair-to-poor color
Actual - By visual inspection
P - Predicted

detecting peeled (yellow) seeds as discussed earlier. Exclusion of yellowish green or light brown seeds from the image would essentially make the borderline RGCLR samples appear as GNCLR. It is expected that improvements in accuracy of detecting peeled seeds would enhance the system performance.

Overall, the online system performed very well on samples from both crop years. The MNN classifier developed with the 1998 samples also worked well for the 1999 samples without re-training. This demonstrates the robustness and universality of the machine vision system developed. This system takes about 23 seconds, on the average, to grade one sample. The most time consuming part is scanning that takes about 20 seconds. Image processing and decision making only takes 3 seconds (with image displays) which could possibly be reduced to less than 1 second without displaying intermediate steps.

These results show a very strong potential for predicting lentil color and grade using an inexpensive and portable machine vision system. The machine vision software and classifier can be implemented on a laptop computer. Although different makes and models of scanners exhibit huge variations in terms of color distribution of the scanner-generated images, scanner matching is possible (Shahin and Symons 2000). Thus, the currently used large and high quality scanner could be replaced by a smaller and less expensive model providing only the level of information required for lentil classification. This would allow a cost-effective solution to be provided to a wide variety of users, ranging from producers through grain elevators to the Canadian Grain Commission. The consistency and repeatability of this approach to grain grading, eliminating the personal bias between buyer and seller, would put grain trading on an even platform. While the grade provided may occasionally be in error, the machine vision system will give a consistent response. This alone is advantageous to the grower.

CONCLUSIONS

This research has demonstrated that a flatbed scanner based machine vision system can be used for grading lentils by color. Based on the results of this study, the following conclusions can be drawn:

1. A flatbed scanner may be used as an alternative imaging system to detect color variations associated with different grades of lentils.
2. Image analyses techniques provided useful image features related to sample grade. Color and texture features were good predictors of the color grade.
3. Statistical and neural classification approaches achieved comparable results. The online grading system with a neural classifier achieved over 90% prediction accuracy.

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