Lentil type identification using machine vision

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Shahin, M.A. and Symons, S.J. 2003. **Lentil type identification using machine vision**. Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **45**: 3.5-3.11. A machine vision system (TrueGrade^T) was used to identify the type (variety) of Canadian lentils from bulk samples. The samples were presented to the instrument in a clear transparent sample tray, and the sample was imaged using a linear array device. The LentilScan© software in TrueGrade^T separated touching kernels facilitating size measurement using mathematical morphology operations. These seed size measurements, when combined with colour attributes of the sample, segregated five lentil varieties commonly grown in Canada with an accuracy approaching 99%. The complete analysis process, from pouring the seed sample into the tray to receiving a result, took about 30 seconds, of which less than 1 second was for image processing and lentil type identification. The remainder of the time was consumed gathering user input and scanning the sample. **Keywords:** lentil, machine vision, image, classification.

Un système d'imagerie artificielle (TrueGrade^T) a été utilisé pour identifier le type (variété) de lentilles canadiennes à partir d'échantillons en vrac. Les échantillons ont été soumiss à l'appareil dans un contenant transparent où ils ont été visualisés par uninstrument à balayage linéaire. Le logiciel LentilScan© du TrueGrade^T séparait les grains en contact facilitant ainsi l'estimation de lataille par des opérations mathématiques de représentation morphologique. Ces mesures detaille des grains, lorsque combinées aux attributs de couleurs deséchantillons, ont permis d'identifier cinq variétés de lentillescommunément cultivées au Canada avec une précision approchant 99%. Leprocessus complet d'analyse, de la mise des lentilles dans le contenantd'échantillonnage jusqu'à la production des résultats ne prenait qu'environ 30 secondes, desquels moins d'une seconde était requise pour l'analyse del'image et l'identification du type de lentille. Le reste du temps étaitconsacré à recueillir les données de l'utilisateur et à balayer l'image del'échantillon. **Mots clés**: lentille, système visuel, imagerie, classification.

INTRODUCTION

Canada exports about 2.7 million tonnes of lentils annually and this is increasing. In Canada, 95% of the lentil production area is in southern Saskatchewan where several different types of lentil are grown (www.pulsecanada.com). The appearance of the seed due to colour and size is the characteristics of most interest to the customer and hence the principle components in determining value. Appearance can be evaluated as the combined effects of colour, colour uniformity, discolouration, disease, and size. The visual assessment of appearance is detailed in the Official Grain Grading Guide (Anonymous 1998). The bulk of the lentils produced in Saskatchewan are large green types. Canada has mostly exported large green lentils of the variety 'Laird' (6 to 7 mm) and small green lentils of the variety 'Eston' (4 to 5 mm) and these names are recognized as trade types (www.pulsecanada.com). Newer green seeded varieties typically have a size between these two traditional types. Thus, it is no longer easy to visually tell the lentil types apart. The requirement for accurate type identification is evident, since different markets favour different types and failure to maintain segregation and identity of the different types leads to loss in value. This is made additionally complex by the simple fact that the lentil seeds change colour upon storage and turn from green to brown as they oxidize.

Uniformity of appearance of the sample is critical to market acceptance of the product. Such a characteristic can only be successfully evaluated, either visually or by instrumentation, when a large surface of the product is viewed. The use of commonly available colorimeters can provide adequate spot colour information, but they fail to provide analysis of variability of the colour components, unless multiple probes or replicates of the sample are examined. This approach is tedious and only provides colour information, one aspect of lentil type identification and grading.

Within each type of lentil, the quality is visually described as a 'grade'. The current inspection practice is to use colour reference prints (Symons and VanShepdael 1994) as visual guides to the minimum acceptable colour for each of four grades. The minimum acceptable level is set by an industry committee based upon review of actual samples and reflects sample appearance, of which colour is one of the major effects. These reference guides are only available for the green 'Laird' and 'Eston' lentil types. Other lentil types have different colour requirements. Machine vision has been successfully used for the objective classification of these colour grades in all types of lentils (Shahin and Symons 2001a) with LentilScan©, a software package developed at the Canadian Grain Commission (CGC). The TrueGrade^T (Hinz Automation, Saskatoon, SK) instrument uses LentilScan© software that has different colour classification models to grade each lentil type. The LentilScan© software, in its current form, selects the appropriate model based on user input. An error in specifying the lentil type may potentially lead to a wrong assessment of the colour grade due to the use of an incorrect colour model. Though chances of such an error by experienced inspectors are rare; the CGC does not guarantee type assignments by its inspectors. Automated and accurate type identification by the vision system would be commercially most beneficial for international trade.

Machine vision techniques have been widely used for inspection of agricultural products such as fruits (Shahin et al. 1999a; Schatzki et al. 1997), vegetables (Shahin et al. 1999b; Tollner et al. 1994), and grains (Wan 1999; Liao et al. 1994). Measurements of morphological, optical, and textural features of various grain types including wheat (Neuman et al. 1987;

Table 1. Lentil types and number of samples scanned for type identification.

Lentil type	Size	Colour	Total samples	Training set	Test set
Laird	large	green	530	264	266
Eston	small	green	210	107	103
Redwing	small	red	38	22	16
Crimson	small	red	74	46	28
Richlea	medium	green	60	30	30
Total samples			912	469	443

Symons and Fulcher 1988a, 1988b; Zayas et al. 1989), corn (Paulsen et al. 1989), canola (Hehn et al. 1991), and lentils (Shahin and Symons 2001a, 2001b) have been reported for grain classification. Sapirstein et al. (1987) classified clean wheat, barley, oats, and rye kernels with reasonably high accuracy. Shatadal et al. (1995) identified wheat and barley kernels from large seeds (peas, beans, lentils) and small seeds (canola, mustard, flaxseed) usually found in grain samples. Machine vision systems are more accurate and efficient in measuring dimensions of seeds than trained inspectors working with a microscope (Churchill et al. 1992).

Machine vision systems for grain identification have been used mostly under controlled laboratory conditions. Generally, most applications require that the seeds be well separated, requiring a tedious and laborious manual operation especially when a large number of seeds in a representative sample of grains are to be analyzed. Some researchers (Casady and Paulsen 1989; Jayas et al. 1999) have developed automatic seed positioning systems for placing individual grain kernels under a camera for image acquisition. Combining such a seed presentation device with the machine vision system, however, will make the overall system more expensive and less portable.

The objective of this research was to develop an effective and robust classification system that could consistently identify bulk lentil samples as to type. Specific objectives were to:

1. Identify image features that can be related to lentil type and apply image processing methods to measure these features of interest from the images of the bulk lentil samples.
2. Analyze the features of interest for their discriminatory power, and test the performance of selected features by using rule-based and statistical (parametric and non-parametric) classification techniques.

MATERIALS and METHODS

Hardware and software

The TrueGrade^T hardware consists of a flatbed scanner (ScanMaker 4, Microtek, Denver, CO), a personal computer with Pentium II processor, and a colour monitor for online image display and user interaction. The scanner unit is encased in a housing providing a 220 x 220 mm window. The remaining glass platen is blacked out. The sample is placed in a clear bottom tray and this is placed over the scanner window for image acquisition as described below. The LentilScan$^©$ software is based on a TWAIN-compliant scanner controller (Scan-Wizard, Microtek, Denver, CO) for image acquisition and an image-processing library (KS-400 V3.0, Carl Zeiss Vision, Oberkochen, Germany) for image processing and feature measurements.

Lentil samples and image acquisition

During the crop year 1999, a total of 912 samples of different lentil types (Table 1), were collected and scanned using a flatbed scanner based vision system (TrueGrade^T, Hinz Automation, Saskatoon, SK). The lentil samples were scanned and assigned to either the training or test sets through random assignment. The training set was used to develop the classifier models, while the test set was used to evaluate the models developed.

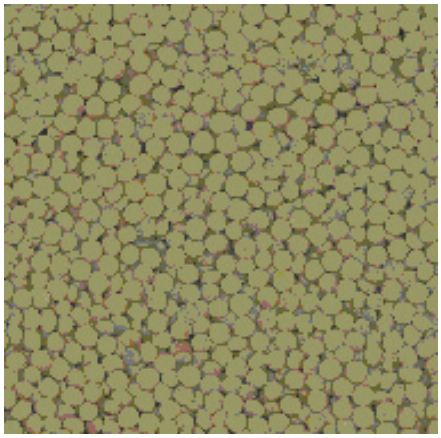
The five major lentil types used in this study can be considered as large, medium, or small and as green or red. Nearly equal number of samples representing each of the four colour-grades (good natural colour; reasonably good colour; fair colour; poor colour) for each lentil type were included in this study. These samples of about 800 g each were imaged on the same day they were graded to avoid complications that could arise from colour changes due to oxidization during storage.

For image acquisition, each sample was poured into a clear plastic sample holder and the under surface imaged. The sample holder (220 x 220 x 50 mm) was machined in a clear plastic and covered the width of the scanner bed. An 800-g sample filled it 25 to 30 mm deep. A non-reflecting black sheet covered the remainder of the scanner bed. This configuration allowed imaging on a bench with ambient room lighting. For each of the samples, a 512 by 512 pixel image window was captured at a resolution of 100 dpi from the centre of the sample tray. Higher scanner resolutions did not provide any information advantage for this kind of application (Shahin and Symons 1999).

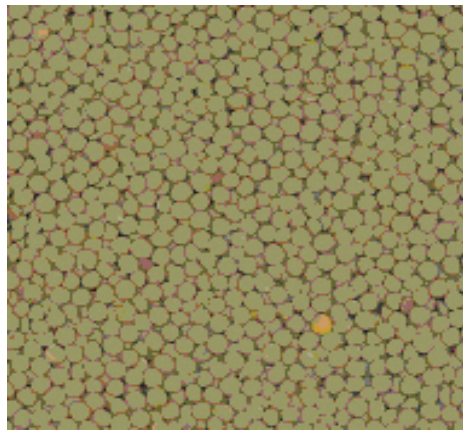
Features of interest

Visual appearance of various lentil types indicates that seed size and colour are good features for segregating different lentil types (Fig. 1). Laird lentils have large green seeds that can be separated rather easily based on seed size from smaller lentil types such as Eston, Redwing, and Crimson. Within the smaller seeded types, there are distinctive colour features. Laird and Richlea types are close in both size and colour. According to experts, however, ”Richlea lentils are about 3/4 the size of the typical Laird lentil and are also generally slightly lighter in colour” (Personal communication: Larry Michta, Senior Inspector, CGC Inspection, Saskatoon, SK). Therefore, seed size, colour, or a combination of both may separate Laird and Richlea lentils. Minor colour and size differences may have a significant effect on image texture.

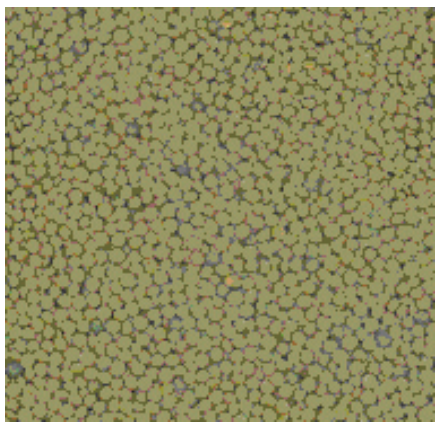
Colour, colour uniformity, and texture (Haralick et al. 1973) features were measured in the original image of a bulk sample using the LentilScan$^©$ software (TrueGrade^T system) based upon the measurement functions available in the KS-400 image-processing software library. The mean colour (hue) measured from the image represents the overall colour of the sample. The image areas corresponding to shadows and peeled and damaged seeds were excluded from colour measurements (Shahin and Symons 2001a). Peeled seeds appeared yellow in green lentils



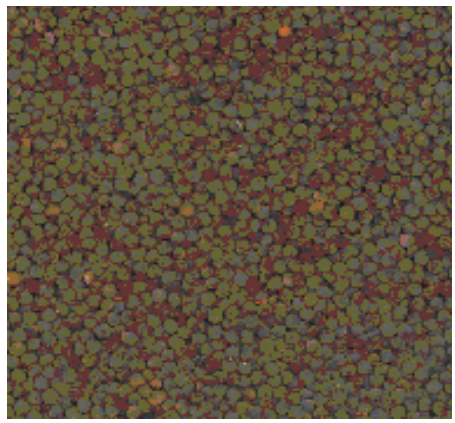
(a) Laird



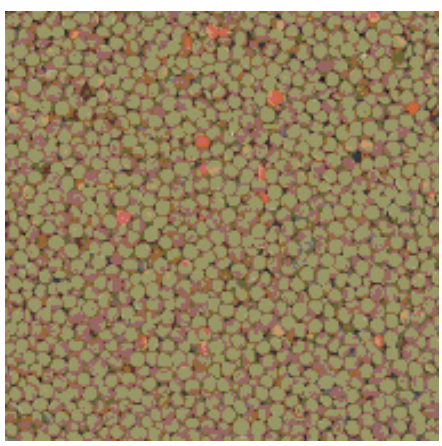
(b) Richlea



(c) Eston



(d) Crimson



(e) Redwing

Fig. 1. Images of various types of lentils differing in size and/or colour.

and orange in red lentils. Damaged seeds appeared dark brown. Colour segmentation (independent segmentation in each of the RGB planes) was used to identify those seeds that were visually confirmed by senior grain inspectors (CGC, Winnipeg, MB). Red and green lentil types required different threshold values for segmentation. Based on preliminary lab tests, the segmentation criteria were defined in LentilScan© over all grades for each lentil type.

To measure the size of seeds in the sample required that the seeds be singulated. This was accomplished through morphological operations. Successive erosion followed by ultimate dilation was used to separate and define seed boundaries. To ensure that only the size of singulated objects (seeds) was measured, a shape factor SF as defined in Eq. 1 was computed for each of the objects in the image.

$$SF = 4\pi \frac{A}{P^2} \qquad (1)$$

where:

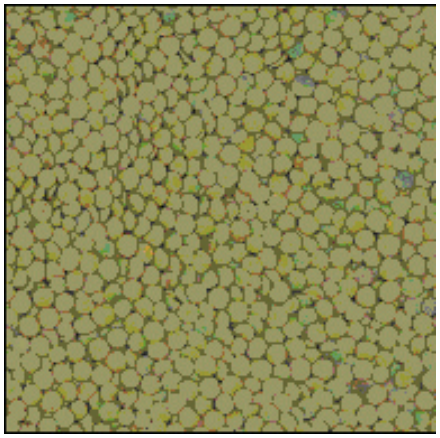
A = area of the object being measured, and

P = perimeter of the object being measured.

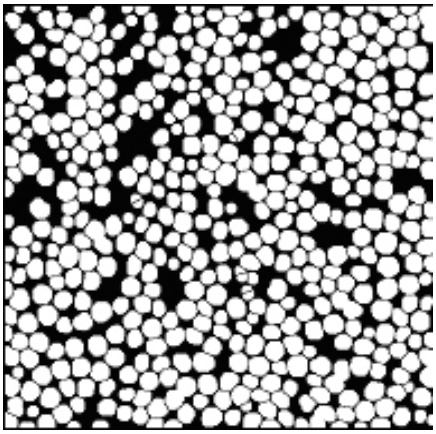
Only nearly circular objects (SF > 0.9) were measured and included in the data set. The mean seed size in a sample was determined as an average of these measurements. Seeds touching the image boundary were excluded using a pre-defined KS-400 frame function as they represent only partial objects (cf. Fig. 2b to 2c and 2e to 2f).

Lentil type identification

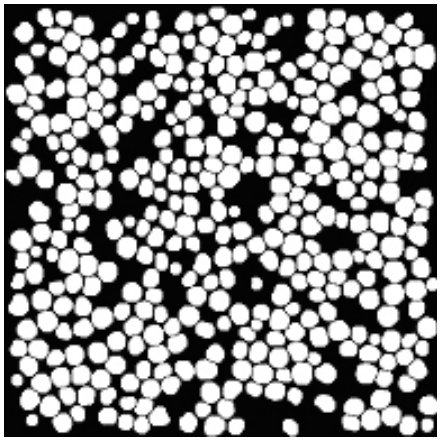
Preliminary investigations had suggested that the mean seed size (area) (Fig. 3) and mean colour (Fig. 4) of seeds in the image provided sufficient information to segregate all five types of lentils considered in this study. A rule-based classifier was built for lentil type identification based on mean seed area and colour. Using IF-THEN rules, three groups of lentils - large (Laird), medium (Richlea), and small (Crimson; Eston; Redwing) - were identified based on mean seed area in each image. The small-seed lentils were then separated based on the mean colour of seeds in an image. The KS-400 software colour library allows colour (hue) to be measured as a grey value between 0 and 255.



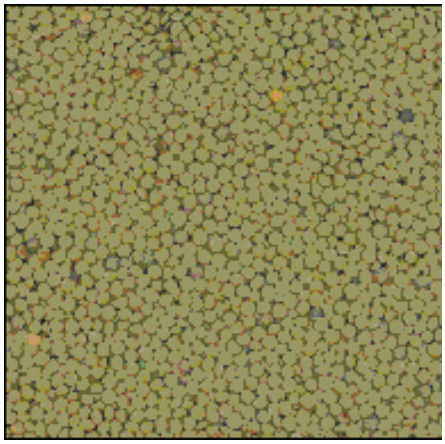
(a) Image of Laird lentils



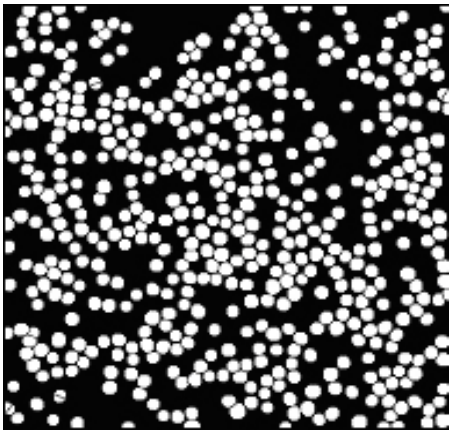
(b) Image 'a' after seed boundary separation with morphological processing.



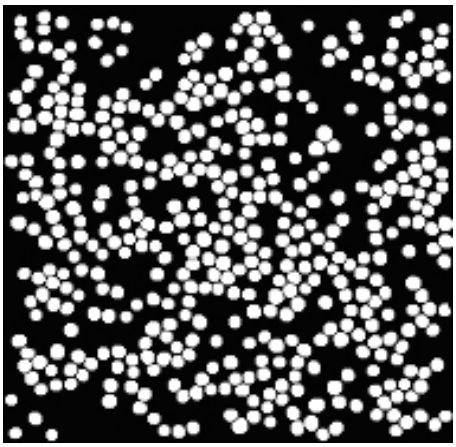
(c) Image 'b' after removing non-circular and boundary touching seeds.



(d) Image of Eston lentils



(e) Image 'd' after seed boundary separation with morphological processing.



(f) Image 'e' after removing non-circular and boundary touching seeds.

Fig. 2. Successive morphological operations can effectively separate seed boundaries for both large (a-c) and small (d-f) seeds required for size measurements.

The training data set was used to determine the threshold values for colour and size while the test data set was used for performance evaluation of the classifier. Performance was judged based on overall accuracy of prediction and class-wise error of prediction (misclassification).

The KS-400 software measurement library has over 200 possible measurement options. Based upon experience, combinations of these features were added to the measurement set to determine if the accuracy of the classifier model could be improved. Using the SAS procedure STEPDISC (Ver. 6.12), these additional measurement features were evaluated as potential candidates for lentil type identification. Statistical classifier models were developed including linear discriminant analysis, quadratic discriminant function, and non-parametric analysis using k-nearest-neighbors and normal-density-kernels. The training data set was used for developing the classifier models and the test data set was used for testing these models. Performance of the statistical classifiers was compared with that of the rule-based classifier for the test data set.

RESULTS and DISCUSSION

The selection of parameters for the discrimination of features within the image is based upon experience and co-operation and advice of senior grain inspectors at the CGC. The objective is to have a standard and repeatable set of parameters so that lentil types can be consistently identified between TrueGrade^{T} instruments. The reference parameters were defined on a single system, which was shown to be stable within short time frames (Shahin and Symons 1999) and has proven to be stable over a period in excess of a year by reference to a standard Q60 colour chart (Kodak, Rochester, NY). Unfortunately, it is not possible to store lentil

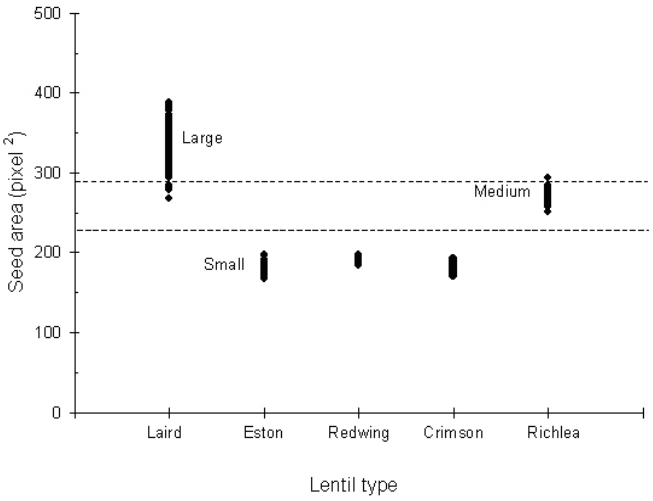


Fig. 3. Separation of lentil types based on the mean seed size in the image of a sample.

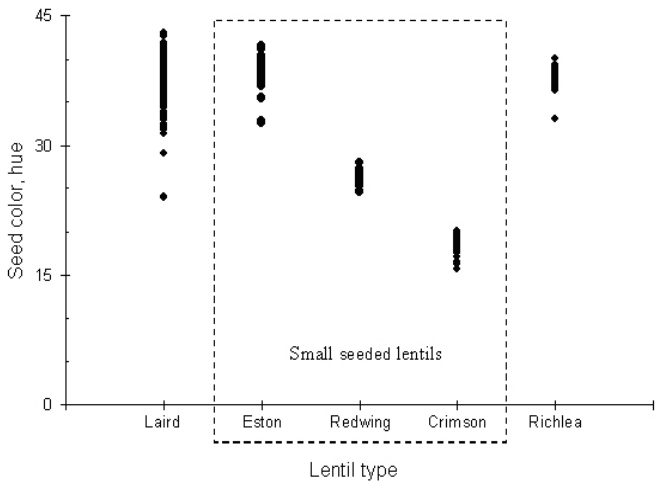


Fig. 4. Separation of small lentils based on the mean colour of seeds in an image of a sample.

samples for such a period without a change in colour, so seed samples cannot be used repeatedly over such a long time frame. Samples from successive crop years, graded by the same inspectors each year did demonstrate consistency in type identification. Using an image of a Kodak Q60 chart generated on this reference system as the 'gold reference' for all subsequent work, differences between scanners were matched, using look-up tables internally generated in the LentilScan© software, to this 'gold standard' (Shahin and Symons, 2000). This approach to calibration ensures absolute matching between systems using image matching techniques, without requiring a numerical description of a colour standard, and the errors associated with determining such measurements (Shahin and Symons 2003).

Morphological operations successfully separated the seed boundaries for seed size measurements from the bulk sample images (Fig. 2). Seed size measurements by this method were compared to the diameter of the seeds measured with a graduated caliper. There was a close agreement between the two methods (Shahin and Symons 2001b). Successive erosion and ultimate dilation operations worked for both large and small seeded lentils (Fig. 2b, 2e). The condition of circularity of objects (SF>0.9) excluded most of the unwanted objects from entering the data set, i.e., seeds at the image boundary, seeds with joined boundaries, and seeds positioned incorrectly were not measured. A few apparently non-circular blobs present in the processed image though undesirable are inevitable. While setting a tighter condition of circularity could remove these 'undesirable' objects, this can also remove some desirable blobs as lentils themselves are not perfectly circular. Figures 2c and 2f represent the final processed images used for size measurements. Success in separating seed boundaries kept the machine vision system simple and cost effective. It allowed for size measurements from the bulk sample images eliminating the need for a seed presentation or separation device that would add to the cost and complexity of the vision system.

Table 2. Performance of the rule-based classifier using mean seed size and mean seed colour (hue) in an image for separating five types of lentils.

Data set	Overall accuracy (%)	Missclassification* (%)	
		Laird to Richlea	Richlea to Laird
Training	98.93	1.52	3.33
Testing	98.87	1.50	3.33

*Misclassification occurred only between Laird and Richlea lentils; classification of Crimson, Eston, and Redwing type lentils was 100% accurate.

Analyses of the individual image features indicated that the mean seed size (area) and the mean seed colour (hue) in the image when combined into a rule-based classifier, can be used to identify all five types of lentils. Seed area separated large (Laird) and medium (Richlea) sized lentils from the small seeded ones (Crimson, Eston, and Redwing) as shown in Fig. 3 where each point represents the average seed size in an image of a sample. In comparison to the other four lentil types, Laird lentils have a wide size range, the result of being the 'grandfather' lentil variety in western Canada. While in most cases, grain inspectors can separate the Laird and Richlea types based upon size; this is not always possible. Richlea and Laird lentils have different mean sizes, but are not clearly separable due to the spread of size within each type (more so in Laird) leading to some size overlap. Hue, determined as the overall colour of seeds in the image, separated the types within the small seeded Crimson, Eston, and Redwing lentils (Fig. 4). When using two features (seed area and hue) as the input variables, the rule-based classifier identified all five varieties with an overall accuracy approaching 99%. Classification of small seeded lentils was 100% accurate, however a small percentage of Laird samples were misclassified as Richlea (1.50%) and vice versa (3.33%). The seemingly high percentage of misclassification for Richlea lentils is based on the misclassification of 1 out of 30 samples and is expected to go down as the number of Richlea samples in the database increases. Results were similar for both the training and test data sets (Table 2).

Table 3. Performance of statistical classifiers with 15 input variables for separating five types of lentils.

Method		Data set	Overall accuracy (%)	Misclassification* (%)	
				Laird to Richlea	Richlea to Laird
LDA**		Training	99.15	1.52	0
		Cross-validation	99.15	1.52	0
		Testing	98.65	2.26	0
QDF		Training	99.79	0.38	0
		Cross-validation	98.51	0.38	20
		Testing	98.87	0.38	13.33
KNN	k=2	Training	99.36	1.14	0
		Cross-validation	99.36	1.14	0
		Testing	98.65	1.50	6.67
	k=4	Training	99.15	1.52	0
		Cross-validation	98.72	2.27	0
		Testing	98.87	1.88	0
	k=6	Training	98.51	2.65	0
		Cross-validation	98.51	2.65	0
		Testing	98.51	2.65	0
NDK	R=0.1	Training	100	0	0
		Cross-validation	98.93	1.14	6.67
		Testing	98.65	0.75	13.33
	R=0.5	Training	100	0	0
		Cross-validation	98.72	1.52	6.67
		Testing	99.36	1.13	0
	R=0.9	Training	99.79	0.38	0
		Cross-validation	99.15	1.52	0
		Testing	99.10	1.50	0

* Misclassification occurred inly between Laird and Richlea lentils; classificatin of Crimson, Eston, and Redwing type lentils was 100% accurate.
**LDA = Linear Discriminant Analysis KNN = K-Nearest Neighbors
QDF = Quadratic Discriminant Functions NDK = Normal Density Kernel with radius R

Several statistical classifiers were tested based upon the selection of the best 15 features using stepwise discriminant analysis (Table 3). For each of the four models, the training set was classified with greater than 99% accuracy and the test data set with better than 98% accuracy. These results were comparable to the results obtained using the simple rule-based classifier. These results show that the simple rule-based classifier using mean seed size and colour (hue) measurements provide sufficient accuracy for practical use without the additional computational overhead of measuring multiple features and running a complex statistical classifier. A small percentage of misclassification of Laird and Richlea samples seems unavoidable mainly because of physical resemblance of these two varieties. It also assumes that the samples used were correctly identified in the first instance, which for the odd visually indistinguishable sample may not be true. By adjusting the boundary values in the rule-based classifier, Richlea samples were identified with 100% accuracy, with a concurrent increase in the misclassification of Laird samples, from 1.5% to 2.3%. From a practical perspective, slight misclassification of both Laird and Richlea was favoured over this latter result.

Laird lentils represent one of the initial lentil varieties released for growth in Saskatchewan and this is indicated by the relatively variable seed size (Fig. 3) resulting from many generations of seed. In contrast, new varieties of green lentils introduced by the Crop Development Center (CDC, Saskatoon, SK) have much tighter seed size distribution based upon the few samples we have measured (Fig. 5). The development of new varieties to meet specific market demands, particularly for specific seed size, can only but increase the probability that instrumental type or variety identification will be possible.

Using the rule-based classifier, the entire automated process took about 28 s to identify one sample on a PII personal computer. The major proportion of this time, (27 s) was the scanning time; software based analysis took only 850 ms. This suggests that lentil type identification can be combined with an existing colour grading system such as the LentilScan© software. As an add-on module, combined with lentil grading software, this system could identify a lentil sample by type in less than a second, and then use this information to select the appropriate grading module for the lentil sample under evaluation.

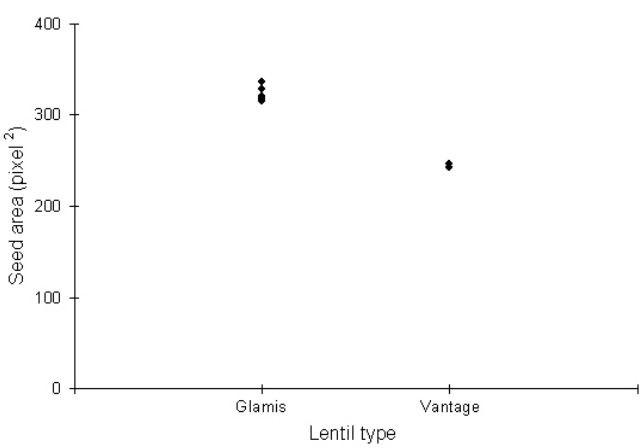


Fig. 5. Seed size of new green lentil types.

CONCLUSIONS

The following conclusions were drawn from this study.

1. Morphological erosion followed by ultimate dilation can effectively separate seed boundaries to facilitate seed size measurements on bulk lentil samples.
2. The mean seed size and the overall colour of a sample can accurately predict lentil type using a rule-based classifier.
3. The LentilScan© software in the TrueGrade™ instrument has the potential to provide automated identification of lentil type.

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