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Grain sample quality assessment using Intechn and Unscrambler platforms

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Abstract: *A comparative analysis of the results obtained in quality assessment of maize grain samples using the INTECHN and Unscrambler platforms are presented in this paper. The INTECHN platform is developed within the frame of the research project "Development of Intelligent Technologies for Assessment of Quality and Safety of Food Agricultural Products", founded by the Bulgarian National Science Fund. The sample elements are divided in nine quality groups according to their surface features, which are related to the surface color and surface texture. The assessment of these features is accomplished using an analysis of the object reflectance spectra. Three different INTECHN approaches are applied for feature extraction from spectra and for data dimensionality reduction: principal component analysis and combinations of two kinds of wavelet analyses and principal component analysis. Three classifiers, based on radial basis elements, are used for classification of the maize grain sample elements. The principal component analysis and the three Unscrambler classifiers (Linear discriminant analysis, Soft independent modeling of class analogy and Support vector machine) are used as referent tools. The validation, training and testing errors of the two platforms are evaluated and compared.*

Keywords: grain sample quality assessment, feature extraction, spectra analysis, classification.

Abbreviations: INTECHN – Abbreviation of the research project, NIR– near infrared reflectance, LDA – linear discriminat analysis, SVM – support vector machines, SIMCA – soft independent modeling of class analogy, PCA – principal component analysis

Introduction

According to the Bulgarian Government Standards the main characteristics of the grain quality are: grain appearance (e.g. shape and color), smell, flavour, moisture content, presence of impurities, etc. The whole grains with appearance, shape and color inherent for the variety and hybrid, as well as the broken grains bigger than the half of the whole grain, are considered to be standard. There are several groups, which are considered as grain impurities: broken grains smaller than the half of the whole grain; heat-damaged grains, small, shriveled and green grains; sprouted grains, moldy grains, infected (with *Fusarium*) grains. The group of the non – grain impurities consists of: corn-cob particles, leaf and stem fractions, pebbles, soil, sand, dust and metal particles, smutty grains, as well as harmful elements (bunt).

Grain visible features, related to the object surface color and texture characteristics are evaluated in this study. The grain sample elements are distributed in the following main quality groups: grains whit inherent for the variety color, heat-damaged grains, green grains, mouldy grains, smutty grains, infected (with *Fusarium*) grains, sprouted grains and non grain impurities. The grain sample characteristics presented above have visible symptoms on the grain surface. The main indications for the quality of grain samples are related to the surface color and surface texture of the objects in a grain sample. Typically, a number of these characteristics are visually assessed by an expert, which is slow and error-prone. This method for assessment presumes a computer vision system (CVS) to be used for evaluation of big part of these quality features (Luo et al., 1999; Liu and Paulsen, 2000; Brosnan and Sun, 2003; Mladenov et al., 2011). There are many materials published, in which color and texture analyses are used to assess some particular quality features like authenticity, variety, infections, germination, etc.

Some preliminary investigations (Mladenov et al., 2011) showed that the analysis of object color images could not give sufficiently precise assessment of some grain sample elements, like infected grains, mouldy grains and non grain impurities. This is determined by the fact that in comparison with the normal grains, not only color features of such objects are changed, but the surface texture are changed too. It is difficult to detect this change using a computer vision system.

Visible (VIS) and near infrared (NIR) spectra analyses are applied in the assessment of different grain quality features (Huang et al., 2008). They are mainly used in tasks, related to the determination of qualitative and quantitative features, like grain composition, dry matter content, moisture content, starch, protein, glutenin, vitamins, toxins, minerals content, as well as to the detection of grain infections. Different maize starch yield calibration models are developed for predicting maize starch content (Paulsen et al., 2003; Paulsen and Singh, 2004). Baye et al. (2006), use single-kernel near infrared spectroscopy (NIRS) to accurately predict the internal kernel composition. Dowell et al. (2006), use NIRS analysis for predicting protein content, moisture content and flour color *b** values. Wesley et al. (2001), develop a method for predicting the protein composition using NIR spectroscopy. Miralbés (2003), analyses wet gluten, dry gluten, moisture, protein, and alveograph parameters (W, P, and P/L) of whole wheat using NIR transmittance spectroscopy. Modified partial least squares models on NIR spectra (850−1048.2 nm) are developed for each constituent or physical property. The best models are obtained for protein, moisture, wet gluten, and dry gluten with r^2 = 0.99, 0.99, 0.95, and 0.96, respectively.

The spectra analysis is used for the detection of different grain

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infections. The determination and prediction of the content of ergosterols and different kind of mycotoxins like aflatoxin, fumonisin and other is very important task because mycotoxins are toxic for animals and humans. Dowell et al. (2002), use reflectance and transmittance VIS and NIR spectroscopy to detect fumonisin in single corn kernels infected with *Fusarium verticillioides*. They classify accurately corn kernels as fumonisin positive or negative, respectively. A method for determination of *Fusarium* graminearum infection is proposed in Kos et al. (2003). The ergosterol and the toxin deoxynivalenol in corn kernels can be determined using this method. The classification accuracy is up to 100% for individual samples. Pearson et al. (2001), evaluate transmittance spectra (500 to 950 nm) and reflectance spectra (550 to 1700 nm) as tools for aflatoxin determination in single whole corn kernels. They use discriminant analysis and partial least squares regression for spectral data processing. The best results are obtained using two feature discriminant analyses of the transmittance data. Peiris et al. (2010), propose a NIRS method for estimation of sound kernels and *Fusarium*-damaged kernels proportions in grain and for estimation of deoxinivalenol levels. The method classifies sound and *Fusarium* damaged kernels with an accuracy of 98.8 and 99.9%, respectively. Ruan et al. (2002), develop a neural network based method for deoxynivalenol levels in barley using NIRS from 400 to 2400 nm. They analyse NIR spectra of barley samples with different deoxynivalenol levels from 0.3 to 50.8 ppm. Girolamo et al. (2009), use Fourier transform NIRS for rapid and non-invasive analysis of deoxynivalenol in durum and common wheat. A qualitative model for discrimination of blank and naturally contaminated wheat samples is developed. Classification accuracy of the model is 69% of the 65 validation samples.

NIR spectroscopy is applied for assessment of grain moisture level too. Mahesh et al. (2010), present a new method using NIR hyperspectral imaging system (960–1,700 nm) to identify five western Canadian wheat classes at different moisture levels. The authors find that the linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) can classify moisture contents with classification accuracies of 89–91 and 91–99%, respectively, independent of wheat classes. Once wheat classes are identified, classification accuracies of 90–100 and 72–99% are observed using LDA and QDA, respectively, when identifying specific moisture levels.

Different methods like Principal Component Regression, Partial Least Squares Regression, Principal Component Analysis (PCA), Hierarchical Cluster Analysis and other methods are used for developing a model to predict a property of interest, as well as for feature extraction and large and complex data reduction. Methods like K-Nearest Neighbors (KNN), Linear Discriminat Analysis (LDA), Cluster Analysis, Support Vector Machines (SVM), Neural Networks (NN), and Soft Independent Modeling of Class Analogy (SIMCA) are used for assessment of different grain features using data from grain spectra.

The goal of the paper is to present and to compare the results in grain sample quality assessment using the INTECHN and Unscrambler referent platform. The assessment of quality features of the sample elements is accomplished using reflectance spectroscopy. In contrast to the investigations cited above, which are related to the grain composition assessment, grain characteristics, which have visible symptoms on the grain surface, are analyzed in this study. Some of the main INTECHN platform methods tools for feature extraction, class modeling and grain sample element recognition are presented too.

Materials and methods

1. Classification of the grain sample elements

The task for categorization of the grain sample elements is a typical classification task. It includes the following steps: representation of spectral data, development of class models and association of an unknown object with one of the models defined.

1.1. Features extraction from spectra

The spectral characteristics of grain sample elements are obtained using QE65000 (Ocean Optics, USA) spectrophotometer. Each characteristic is a vector with about 1500 components. Within the frames of the INTECHN platform Principle Component Analysis (PCA) and combination of Wavelet descriptions and PCA are used for extracting typical features from object spectral characteristics and for input data reduction. It is foreseen the following Wavelet coefficients are used: Wavelet1- detail coefficients and Wavelet2- approximation coefficients. The operator can select one of the following wavelet functions: Haar, Daubechies2, Coiflet2, Symlet2. The level of decomposition can vary from m=1 to m=4. The most informative wavelet coefficients are chosen using PCA method. The PCA method is used for feature extraction in the Unscrambler platform.

1.2. Grain sample classification groups

In conformity with their surface characteristics the grain sample elements are distributed in the following groups (classes): 1cc-grains whit inherent for the variety color, back side; 2cc-grains whit inherent for the variety color, germ side; 3cc -heat-damaged grains; 4cc-green grains, 5cc-mouldy grains; 6cc-smutty grains, 7cc - infected (with Fusarium) grains, 8cc-sprouted grains, and 9cc-non grain impurities. The last group is divided in the following sub groups (subclasses): 9cc1-corn-cob particles; 9cc2-leaf fractions; 9cc3-stem fractions; 9cc4-pebbles; 9cc5-soil, and 9cc 6-sand.

Maize grain samples of the Kneja-433 variety are used in the investigation. The Maize Research Institute-Kneja, Bulgaria, produces this variety. The samples are gathered in one corn-growing season of one crop year and from one growing location. Principally, the INTECHN platform presumes the grain kind, variety and hybrid to be specified when we develop a new data base. There is a possibility for the growing location to be specified too. The *Fusarium* infection is selected for assessment due to the fact that such infection is often present in maize crops. If we have to detect another kind of infection, which has visible features on the grain surface, we have to develop a new model of this infection.

1.3. Development of models of grain sample quality groups

The sets of descriptions extracted from grain sample training sets are used for developing the models of grain sample quality groups. Each class model was presented by the class center (the average value of the class training data) and the class boundary surface. The boundary surface was determined through a threshold value of the covariance of the class training data. It is relevant to remark that modes were created only for the first eight groups. A correct model for the 9-th grain group cannot be created because of the fact that the spectral characteristics of elements of this class could be sufficiently different in each subsequent grain sample.

The task for grain sample class modeling was reduced to a task for approximation of the grain class areas. For this purpose, classifiers based on Radial Basis Elements (RBEs) were used. Classifiers, based on RBEs are used in terms of the simplicity of the classification procedure and the accuracy of the class area approximation. Furthermore, if we set an appropriate value of the RBE bias and a minimal threshold Δ of its output, it becomes clear what part of input objects will be included within the class boundary and it is easy to change the dimensions of the particular class *area*.

1.4. Classifiers for class modeling.

The INTECHN classifiers. The following neural classifiers, based on RBEs (Mladenov et al., 2011)*, are used for class model development.*

CSRBE classifier. Only one RBE is used for approximation of each class area. The RBEs centers correspond to class average values obtained from class training sets. The RBEs biases are set in correspondence with standard deviations of the input vectors from the respective training sets. The CSRBE approximates round shaped classes only. To determine to what class the input vector belongs, the output $f_{\omega i}$ with maximum value is chosen. This value has to exceed the threshold value Δ which determines the class areas dimension.

CDRBE classifier. The CDRBE (classifier with decomposing RBEs) *architecture* includes three layers. The first classifier layer consists of m (m is the number of classes) transforming elements, which recalculate input vectors coordinates in local coordinate systems which axes coincide with class axes of inertia. The second layer consists of n x m RBEs which are distributed in m sub layers. The number of RBEs in each sub layer is equal to n (n is the input vectors dimensionality). The RBEs centers coincide with average values of the projections of training sets vectors onto corresponding coordinates of class local coordinate system. The RBEs biases are set in correspondence with standard deviations of respective input vectors coordinates projections ($\sigma_{x1\omega i,}$ $\sigma_{x2\omega i}$...$\sigma_{xn\omega i}$). The third layer consists of m RBEs. The weights of all RBEs are equal (1, 1... 1). The RBEs outputs are the weighted distances of input vector to the centers of non – spherical classes.

The CDRBE classifier gives a possibility to form classes whose dimensions along the directions of separate coordinate axes are different. Changing the RBEs biases and the threshold value Δ we can vary the class shape from sphere to shape close to a parallelepiped.

CRBEP classifier. The CRBEP classifier approximates the class areas using standard (or decomposing) RBEs and takes into consideration the class potentials. The accumulated during classification number of vectors of each of the classes is interpreted as a class potential V_i. The class potential V_i introduces an additional correction Δf_i of the assessment f_i formed by i-th RBE. The effect of the correction comes down to the displacement of the boundary between two overlapping parts of class areas. The displacement depends on the ratio of accumulated number of vectors in each of the classes

The Unscrambler classifiers. The Unscrambler platform uses the following popular classifiers for class modeling: LDA, SIMCA and SVM.

1.5. Classifier validation

The INTECHN classifiers presented above are trained and validated using a specific cross-validation procedure. The goal of the validation is to select appropriate data model for the description of spectral data, appropriate classifier and to obtain the optimal classifier parameters k and k_v. In comparison with the standard cross-validation approach (K fold cross-validation), the INTECHN platform validation is based on the following procedure. In spite of the classifiers create models of the first eight grain sample groups, some elements of the 9cc group are used in classifier validation. This leaded to the limitation of the class area dimensions, which was a precondition a big part of non-grain impurities to be rejected form the classifier. In that case this result was a correct classification.

1.6. Association of an unknown object with one of the models defined.

As it was mention above, a correct model for the 9-th grain group cannot be created. A part of the descriptions of such objects could get into the boundaries of the eight classes defined. A big part of them will get outside the class areas and can be located in a random place in the feature space. These descriptions can be considered as noisy vectors. It can be assumed that the comparatively compact class areas of the objects from the first eight groups are submerged in a noisy environment. Therefore, the task for grain sample element categorization can be interpreted as a task for classification in classes, whose boundaries have definite shapes, dimensions and location in the feature space, and they are situated in a noisy environment.

2. INTECHN platform graphical user interface

INTECHN platform training GUI is used for object classification on the basis of the reflectance spectra analysis. After the choice of object type the operator introduces data of spectral characteristics of selected objects from files. Spectral characteristics are shown in GUI field "Spectral characteristics". Trough activating respective buttons the procedures for feature extraction and data reduction are started. Classes are visualized in the feature space by means of the first tree components of selected feature description. The extracted form class training sets multidimensional vector descriptions are used for classifiers validating and training.

Results

1. Training and testing sets

The classifiers used for the recognition of the grain sample elements are validated, trained and tested with sets presented in Table 1.

2. Classification of the grain sample elements

The results from the classification of the grain training samples using the three INTECHN classifiers and the three data models are presented in Table 2. The classifier validation is implemented in two variants – when the non grain impurities are excluded from and included in the validation sets. The results from the classification of the grain training samples using the three Unscrambler classifiers (LDA, SIMCA and SVM) and PCA data model are presented in Table 3. The classifier training is made in two variants – when the non grain impurities are excluded from and included in the training sets.

The results from the classification of the grain testing samples using the INTECHN and Unscrambler platforms are presented in Table 4 and Table 5 respectively. The data is obtained using the classifier and data model selected, which assure the best classification accuracy.

The classification errors are calculated using the equations:

$e_i = FN_i/(TP_i+FN_i)$ (1)

e_i gives the relative part of objects from some class i, which are assigned incorrectly to other classes k=1...N, where FN_i is the number of elements from the i-th class, which are incorrectly classified in other classes, TP_i is the number of correctly classified elements from the i-th class;

$g_i= FP_i/(TP_i+ Fp_i)$ (2)

g_i gives the relative part of objects from other classes, which are assigned to i-th class, where FP_i is the number of elements from other classes, which are incorrectly classified in the i-th class;

$$e_o = \frac{\sum_{i=1}^{N} FN_i}{\left(\sum_{i=1}^{N} TP_i + \sum_{i=1}^{N} FN_i \right)} \quad (3)$$

e_o (classification error rate) gives the relative part of all wrongly classified objects, were N is the number of classes.

Discussion

Results obtained using the INTECHN platform

The errors of the grain sample testing set classification (1.3% when the non grain impurities are excluded from training/validation sets, and 7.3% when the non grain impurities are included in training/validation sets) are acceptable bearing in mind the specific experimental circumstances and the diversity of the grain sample elements. This result confirms the effectiveness of the developed approaches and procedures for features extraction, classification strategy, classifiers and classifier validation.

The analysis of the results obtained shows that the data model, validation approach and the type of classifier influence on the classification accuracy. For example, if the three data models (PCA, Wavelet1+PCA and Wavelet2+PCA) are used, the training errors are 6.7%, 6.3% and 10.3% respectively using the CDRBE classifier and the non grain impurities are included in the validation.

The INTECHN validation approach (when the non grain impurities are included in the validation procedure, but they are excluded from the training sets) decreases the testing error 3.8 times (from 27.6% to 7.3%) in comparison with the traditional cross-validation approach (when the non grain impurities are simultaneously excluded or included in the validation and training sets).

The choice of an appropriate classifier influences on the classification accuracy too. For example, the training errors obtained using the CDRBE, CSRBE and CRBEP classifiers and PCA data model are 6.7%, 72% and 7.2% respectively.

Results obtained using the Unscrambler platform

The training and testing errors obtained using the Unscrambler classifiers are bigger then the errors obtained by the CDRBE and CRBEP classifiers. For example, the SVM (the Unscramble classifier with the best performance) and the CDRBE training errors are 2.5% and 0.8% respectively, when the elements from the class

Table 1. Training and testing sets

Classes, subclasses	Training sets, number of objects	Training sets, number of objects
1cc - grains whit inherent for the variety color, back side	120	30
2cc- grains whit inherent for the variety color, germ side	120	30
3cc - heat-damaged grains, burned grains	80	20
5cc - mouldy grains	53	13
7cc - infected (with Fusarium) grains	192	48
8cc - sprouted grains	42	11
9cc - non grain impurities:	536	134
9cc1 - corn-cob particles	96	24
9cc2 - leaf fractions	96	24
9cc3 - stem fractions	96	24
9cc4 - pebbles	56	14
9cc5 - soil	96	24
9cc6 - sand	96	24

Table 2. Training results obtained using Unscrambler platform

INTECHN platform training errors e_o,%									
Data model	PCA			Wavelet1+ PCA			Wavelet2+ PCA		
Classifier	CDRBE	CSRBE	CRBEP	CDRBE	CSRBE	CRBEP	CDRBE	CSRBE	CRBEP
Non grain impurities are excluded from validation sets									
	0.8	47.8	0.8	0.3	47.8	0.3	0.8	9.9	0.8
Non grain impurities are included in the validation sets									
	6.7	72	7.2	6.3	72	6.4	10.3	47.8	10.4

Table 3. Training results obtained using Unscrambler platform

Unscrambler platform training errors e_o,%			
Data model	PCA		
Classifier	LDA	SIMCA	SVM
Non grain impurities are excluded from validation sets			
	5.3	8.2	2.5
Non grain impurities are included in the validation sets			
	7.4	26.9	14

Table 4. Classification of the testing sets using the INTECHN platform data model and classifier selected

Non grain impurities are excluded from the validation and testing sets										
Wavelet2+PCA model, CDRBE classifier										
		Actual classes							Errors	
	1	1	2	3	5	7	8	9	g_i,%	e_i,%
Classifier decision	2	**28**	0	0	0	0	0	0	0	6.7
	3	0	**30**	0	0	0	0	0	0	0
	5	0	0	**20**	0	0	0	0	0	0
	7	0	0	0	**13**	0	0	0	0	0
	8	2	0	0	0	**48**	0	0	4.0	0
	9	0	0	0	0	0	**11**	0	0	0
	Num. of objects	0	0	0	0	0	0	**0**		
		30	30	20	13	48	11	**0**	**e_0= 1.3%**	
Non grain impurities are included from the validation and testing sets										
Wavelet2+PCA model, CDRBE classifier										
		Actual classes							Errors	
	1	1	2	3	5	7	8	9	g_i,%	e_i,%
Classifier decision	2	**17**	0	0	0	0	0	0	0	45.4
	3	0	**15**	0	0	0	0	0	0	50
	5	0	0	**4**	0	0	0	0	0	80
	7	0	0	0	**5**	0	0	0	0	61.5
	8	0	1	0	0	**29**	0	0	3.3	39.6
	9	0	0	0	0	0	**4**	0	0	63.6
	Num. of objects	13	14	16	18	19	7	**134**	36.5	0
		30	30	20	13	48	11	134	**e_0= 27.6%**	
Non grain impurities are included in the validation and testing sets										
Wavelet1+PCA model, CDRBE classifier										
		Actual classes							Errors	
	1	1	2	3	5	7	8	9	g_i,%	e_i,%
Classifier decision	2	**25**	0	0	0	0	0	0	0	16.7
	3	0	**28**	0	0	0	0	0	0	6.7
	5	1	0	**17**	1	0	0	0	10.5	15
	7	0	0	0	**9**	0	0	0	0	30.8
	8	1	2	0	0	**46**	0	3	11.5	4.2
	9	0	0	0	0	0	**25**	0	0	18.2
	Num. of objects	3	0	4	2	2	2	**131**	9.0	2.2
		30	30	20	13	48	11	134	**e_0= 7.3%**	

Table 5. Classification of the testing sets using the Unscrambler platform data model and classifier selected

Non grain impurities are excluded from the training and testing sets										
PCA model, SVM classifier										
		Actual classes							Errors	
	1	1	2	3	5	7	8	9	g_i,%	e_i,%
Classifier decision	2	**29**	0	0	0	1	0	0	3.3	3.3
	3	0	**27**	0	0	1	0	0	3.6	10
	5	0	0	**17**	0	0	0	0	0	15
	7	0	0	2	**12**	0	0	0	14.3	7.7
	8	1	3	1	1	**46**	0	0	11.5	4.2
	9	0	0	0	0	0	**11**	0	0	0
	Num. of objects	0	0	0	0	0	0	**0**		
		30	30	20	13	48	11	0	**e_0= 6.6%**	
Non grain impurities are excluded from the training sets and included in the testing sets										
PCA model, SVM classifier										
		Actual classes							Errors	
	1	1	2	3	5	7	8	9	g_i,%	e_i,%
Classifier decision	2	**29**	0	0	0	1	0	3	12.1	3.3
	3	0	**27**	0	0	1	0	0	3.6	10
	5	0	0	**17**	0	0	0	7	29.2	15
	7	0	0	2	**12**	0	0	56	82.9	7.7
	8	1	3	1	1	**46**	0	52	55.9	4.8
	9	0	0	0	0	0	**11**	16	59.3	0
	Num. of objects	0	0	0	0	0	7	**0**	0	88.1
		30	30	20	13	48	11	134	**e_0= 44.7%**	
Non grain impurities are included in the training and testing sets										
PCA model, SVM classifier										
		Actual classes							Errors	
	1	1	2	3	5	7	8	9	g_i,%	e_i,%
Classifier decision	2	**26**	0	0	0	3	0	4	21.2	13.3
	3	2	**24**	0	0	1	0	0	11.1	20
	5	0	0	**8**	0	0	0	3	27.3	60
	7	0	0	3	**3**	0	1	51	94.8	76.9
	8	2	4	5	0	**21**	0	6	44.7	56.2
	9	0	0	0	0	1	**9**	8	50	18.2
	Num. of objects	0	2	4	10	22	1	**58**	40.2	56.7
		30	30	20	13	48	11	134	**e_0= 47.9%**	

9cc are excluded from the validation/training sets. The testing errors of the two classifiers are 6.6% and 1.3% respectively. When the elements from the class 9cc are included in the testing sets, the testing errors were 44.7% and 27.6%.

Similar results are obtained when elements from the 9cc class are included in the validation/training sets. For example, the SVM and CDRBE training errors are 14% and 6.3% respectively. The testing errors of the two classifiers were 47.9% and 7.3%.

Conclusions

An effective approach for grain sample quality assessment is developed. It is based on the analysis of the reflectance spectra of the grain sample elements. The approach is ground on specific methods for feature extraction and for grain sample element classification. Combinations of two kinds of wavelet analyses and PCA are used for extracting appropriate features from object spectra. A method for pattern classification in classes located in a noisy environment, which uses classifiers for class area approximation and a specific approach for classifier validation, is applied for the grain sample element classification.

The effectiveness of the approach developed is confirmed by the results obtained in the recognition of maize grain sample elements under the specific experimental circumstances. The training and testing accuracy are 93,7% and 92.7%, respectively. These results are acceptable bearing in mind the nature of the investigated objects.

The INTECHN platform gives better results in comparison with the Unscrambler referent platform. For example, the SVM and CDRBE training errors are 14% and 6.3% respectively, and the testing errors are 47.9% and 7.3%, when elements from 9cc class are included in the training/validation sets.

The analysis of the results obtained shows that the data model, validation approach and the type of classifier influence on the classification accuracy. For example, if the three data models (PCA, Wavelet1+PCA and Wavelet2+PCA) are used, the training errors are 6.7%, 6.3% and 10.3% respectively using the CDRBE classifier. In comparison with the traditional cross-validation approach, the INTECHN validation approach decreases the testing error 3.8 times (from 27.6% to 7.3%) under specific experimental circumstances. The training errors obtained using the CDRBE, CSRBE and CRBEP classifiers and PCA data model are 6.7%, 72% and 7.2% respectively.

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References

Baye TM, Pearson TC and Settles AM, 2006. Development of a calibration to predict corn seed composition using single kernel near infrared spectroscopy. Journal of Cereal Science, 43, 2, 236-243.

Brosnan T and Sun DW, 2003. Inspection and grading of agricultural and food products by computer vision systems - a review. Computers and Electronics in Agriculture, 36, 193 – 213.

Dowell F, Pearson T, Maghirang E, Xie F and Wicklow D, 2002. Reflectance and Transmittance Spectroscopy Applied to Detecting Fumonisin in Single Corn Kernels Infected with Fusarium verticillioides. Cereal Chemistry, 79, 2, 222-226.

Dowell FE, Maghirang B, Xie F, Lookhart GL, Pierce RO, Seabourn BWS, Bean R, Wilson JD and Chung OK, 2006. Predicting Wheat Quality Characteristics and Functionality Using Near-Infrared Spectroscopy. Cereal Chem. 83, 5, 529–536.

Girolamo AD, Lippolis V, Nordkvist E and Visconti A, 2009. Rapid and non invasive analysis of deoxinivalenol in durum and common wheat by Fourier – Transform infrared spectroscopy. Food Additives and Contaminants, 26, 06, 907-917.

Huang H, Yu H, Xu H and Ying Y, 2008. Near infrared spectroscopy for on/in-line monitoring of quality in foods and beverages: A review. Journal of Food Engineering, 87, 3, 303-313.

Kos G, Lohninger H and Krska R, 2003. Development of a Method for the Determination of Fusarium Fungi on Corn Using Mid-Infrared Spectroscopy with Attenuated Total Reflection and Chemometrics, Analytical Chemistry, 75, 5, 1211–1217.

Liu J and Paulsen MR, 2000. Corn whiteness measurement and classification using machine vision. Transactions of the ASAE, 43, 3, 757 – 763.

Luo X, Jayas DS and Symons S, 1999. Comparison of statistical and neural network methods for classifying cereal grains using machine vision. Transactions of the ASAE, 42, 2, 413-419.

Mahesh S, Jayas DS, Paliwal J and White NDG, 2010. Identification of wheat classes at different moisture levels using near-infrared hyperspectral images of bulk samples, Sensing and instrumentation for food quality and safety, 10, 1007.

Miralbés C, 2003. Prediction Chemical Composition and Alveograph Parameters on Wheat by Near-Infrared Transmittance Spectroscopy, Journal of Agricultural and Food Chemistry, 51, 21, 6335–6339.

Mladenov M, Penchev S, Dejanov M and Mustafa M, 2011. Quality assessment of grain samples using colour image analysis. Proc. of the 8th IASTED International conference on Signal Processing, Pattern Recognition and Applications.

Paulsen MR, Pordesimo LO, Singh M, Mbuvi SW and Ye B, 2003. Corn starch yield calibrations with near-infrared reflectance. Biosystems Engineering. 85, 4, 455-460.

Paulsen MR and Singh M, 2004. Calibration of a near-infrared transmission grain analyzer for extractable starch in corn. Biosystems Engineering, 89, 1, 79-83.

Pearson TC, Wicklow DT, Maghirang EB, Xie F and Dowell FE, 2001. Detecting aflatoxin in single corn kernels by transmittance and reflectance spectroscopy. Transactions of the American Society of Agricultural Engineers, 44, 1247–1254.

Peiris KHS, Pumphrey MO, Dong Y, Maghirang EB, Berzonsky W and Dowell FE, 2010. Near-Infrared Spectroscopic Method for Identification of Fusarium Head Blight Damage and Prediction of Deoxynivalenol in Single Wheat Kernels. Cereal Chemistry, 87, 6, 511–517.

Ruan R, Li Y, Lin X and Chen P, 2002. Non-destructive determination of deoxynivalenol levels in barley using nea-infrared spectroscopy. Applied Engineering in Agriculture, 18, 50, 549-553.

Wesley IJ, Larroque O, Osborne BG, Azudin N, Allen H and Skerritt JH, 2001. Measurement of gliadin and glutenin content of flour by NIR spectroscopy. Journal of Cereal Science, 34, 125–133.

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Todorov N and Mitev J, 1995. Effect of level of feeding during dry period, and body condition score on reproductive performance in dairy cows, IX th International Conference on Production Diseases in Farm Animals, Sept.11 – 14, Berlin, Germany, p. 302 (Abstr.).

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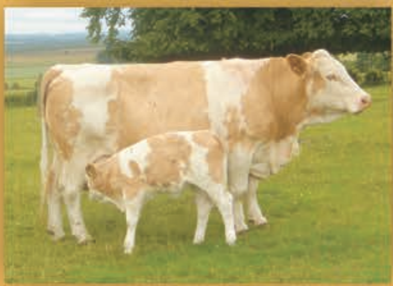

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