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Non-destructive classification and quality evaluation of proso millet cultivars using NIR hyperspectral imaging with machine learning

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ABSTRACT. *Millet is a small-seeded cereal crop with big potential and remarkable characteristics such as high drought resistance, short growing time, low water footprint, and the ability to grow in acidic soil. There is a need to develop non-destructive methods for differentiation and evaluation of the quality attributes of different of proso millet cultivars grown in the U.S. Current methods of cultivar classification are either subjective or destructive, time consuming, not allowing for the whole population to be tested, and requiring trained operators and special equipment. In this study, the feasibility of using near-infrared (NIR) hyperspectral imaging (900-1700 nm) to predict the quality attributes of proso millet (Panicum miliaceum* L.*) seeds as well to classify its different cultivars was demonstrated. Ten different cultivars of proso millet variety, which are the most popular in the US, investigated in this study included Cerise, Cope, Earlybird, Huntsman, Minco, Plateau, Rise, Snowbird, Sunrise, and Sunup. To reduce the large dimensionality of the hyperspectral imaging, principal component analysis (PCA) was applied, and the first two principal components were used as imaging features for building the classification models. The Classification performance showed a test accuracy rates as high as 99% for classifying the different cultivars of proso millet using gradient tree boosting ensemble machine learning algorithm. Moreover, using the partial least squares regression (PLSR) the coefficient of determination (R^2) for quality prediction of proso millet seeds were 0.87, 0.80, 0.83, 0.93, and 0.92 for moisture content, crude protein, crude fat, ash, and carbohydrate, respectively. The overall results indicate that NIR hyperspectral imaging could be used to non-destructively classify and predict the quality of proso millet seeds.*

Keywords. *Millet, Proso millet variety, Hyperspectral imaging, Near-infrared , NIR, Machine learning*

Introduction

Millet is a small-seeded cereal crop with big potential. It has incredible qualities like drought resistance, high protein content (Singh et al., 2017), short growing times (Baltensperger, 2002)(Kalinova & Moudry, 2006), low water requirements (Han, Yang, Wu, & Yi, 2019), and the ability to grow in acidic soil (Niranjan, Prakasha, Meena, Kiran, & Yadawad, 2020). All these qualities allow millet to be a great crop for propagation in arid areas of Africa and Asia, and important for tackling food insecurity in this part of the world (Amadou, Gounga, & Le, 2013). There are nearly 20 different species of millet. In the US, proso millet (*Panicum miliaceum* L.) is the most produced variety of millet, with over 188,180 ha harvested in 2019 (USDA, 2021). Proso millet has many different cultivars from this variety, with some farmers producing more than one cultivar on a single plot of land. This creates an issue of sorting and product consistency. Also, knowing the variety of millet and the proximate content of the product is important for consumers (Zhang, Liu, He, & Li, 2012). Current methods of seed classification use DNA molecular marking technology, visible morphological identification, and protein electrophoresis. All these techniques include their own shortcomings, with some being destructive, time consuming, not allowing for the whole population to be tested, and requiring trained operators and special equipment. These methods for quality detection have some shortcomings. Quality detection is often destructive such as the AOAC methods. These methods are not ideal as they are also time-consuming, not practical for commercial use, and cannot evaluate each individual seed.

Because current methods for identifying millet cultivars and determining its contents are laborious and destructive, other methods need to be implemented to fix these issues. Some nondestructive solutions have been developed, like methods such as spectroscopy (Chen, Ren, Zhang, Diao, & Shen, 2013; Cui-qing, Li-juan, Sheng, & Yu-ming, 2017), spectral vegetation indices (Baath, Flynn, Gowda, Kakani, & Northup, 2021), machine visions (Venkatesan & Sujatha, 2018) and hyperspectral imaging (X. Wang, Li, Zheng, & Wang, 2020). Among these, hyperspectral imaging (HSI) can provide the most information, as it combines the techniques of machine visions and spectroscopy. Machine vision is an automated computer system that visually inspects the sample, operating at visible wavelengths to give a picture of the external view and positions of certain features (ElMasry & Sun, 2010). This, however, cannot give an internal view of the object, missing the ability to detect complex classifications and quality compositions (ElMasry & Sun, 2010). On the other hand, spectroscopy obtains spectral data of a sample from its light absorbance or reflectance. This gives information about the internal components of the sample but does not pinpoint its exact location (ElMasry & Sun, 2010). By combining machine visions and spectroscopy, HSI can obtain a spectrum for each pixel in an object's image, creating a hypercube with spatial dimensions on two axes, and wavelength spectral dimension on the third axis (Manley, 2014). With this added dimension, HSI can provide spectra for every pixel, giving it the advantage to tell more information about the sample (Manley, 2014). This method works especially well for samples whose nature is not homogeneous, such as seeds that have an uneven distribution of internal chemical components (Zhu et al., 2019). With hyperspectral imaging, millet seeds can be accurately classified and qualified.

Various studies have been conducted using hyperspectral imaging to classify millet and other small grain seeds. X. Wang et al. (2020) used visible-near-infrared hyperspectral imaging to classify 480 samples of eight millet varieties with an attention-CRNN model, having an accuracy of 87.5%. This study showed low accuracy and is used less common millet cultivar. To improve upon these results, the number of seeds may need to be increased, the spectra range adjusted, or a different type of machine learning could be used. On top of this, with using cultivars of proso millet, there is more of a commercial application than that of the smaller cultivars Wang et al. uses in their study. Besides the work done by Wang et al., there is very little work done on small cereals like millet in the way of HSI used in for classification. However, this topic has been covered by others using different cereals. Zhang et al. (2012) developed a model to discriminate maize seed types of 330 samples of 6 varieties through hyperspectral imaging in the visible and near-infrared region with 98.89% accuracy. Another study on maize seeds was conducted by Zhao et al. (2018). They used NIR HSI to scan 12,900 seeds of 3 different varieties and created an algorithm that could classify the seeds. Another study on maize seeds was done by Xia et al. (2019). Using visible-near-infrared HSI to scan 1623 seeds of 17 varieties and multilinear discriminate analysis (MLDA) algorithm, they obtained an accuracy of 99.13%. Kong, Zhang, Liu, Nie, and He (2013) identified 225 rice seeds of four different cultivars with classification rates over 80% using near-infrared hyperspectral imaging system.

More work has been done using hyperspectral technology in classifying different kinds of seeds than in predicting proximate qualities and content. Chen et al. (2013) used near-infrared spectroscopy to determine protein, carbohydrates, and fat contents of foxtail millet with a coefficient of determination of validation of 0.94, 0.92, and 0.7, respectively. In another study done by J. Wang et al. (2019), broomcorn millet was scanned using HSI to predict the protein content of the seeds and leaf nitrogen content. Using machine learning and linear regression, the coefficient of determination of the calibration set and validation set were 0.928 and 0.924 respectively. While both studies yield sufficient results, they lack the diversity and range of information that could be displayed by their dataset.

The objective of this experiment is to 1) determine the exact proximate content of different cultivars of proso millet. 2) Create a dataset of spectral data for the seeds. 3) Use this dataset to create a supervised algorithm to classify unknown millet cultivars and 4) predict the proximate content of an unknown millet seed based on the information based in set 1.

Materials and methods

Sample preparation

In this study, ten different cultivars of proso millet seeds were grown and obtained from the University of Nebraska's Panhandle Research and Extension Center in Scottsbluff, Nebraska. Ten common cultivars produced in the U.S. were studied, namely *Cerise*, *Cope*, *Earlybird*, *Huntsman*, *Minco*, *Plateau (waxy var.)*, *Rise*, *Snowbird*, *Sunrise*, and *Sunup*. The seeds were sifted to remove any outside contaminates like stones, dirt, and straw using a Ro-Tap sieve shaker (RX-29, W.S. Tyler, Mentor, Ohio), then dehulled with a modified disc mill (Glenn Mills Inc., Clifton, N.J.) where the stationary disk was replaced with a rubber disk. This minimizes the breakage of the millet and provides a better chance of proper hull removal. The seeds were placed in labeled bags separating each cultivar, then stored in a freezer with a temperature of -70°C. To be prepared for scanning, the seeds were taken out of the freezer and placed at room temperature (about 27°C) for at least 1 hour prior to testing. A total of 500 seeds were counted out from each bag, separated into 10 groups of 50 seeds. These seeds were then scanned by hyperspectral data acquisition, carried out in the Food Engineering lab at Biosystems and Agricultural Engineering Department, University of Kentucky, Lexington, KY, USA. This preparation was then repeated every day until each of the 10 cultivars of millet was tested.

Millet quality determination

To find the proximate content, the samples were first ground by a Quadrumat Junior Mill (C.W. Brabender Instruments Inc., South Hackensack, N.J.). Then, using the AOAC Standard Method, the five qualities measured in each of the cultivars of proso millet were determined: moisture content (Method 925.09), crude protein (Method 920.87), crude fat (Method 920.39), ash (Method 923.03), and carbohydrate (Method 985.29) (AOAC, 2010, Singh et al., 2018).

HSI system and image acquisition

The machine used for hyperspectral data acquisition of the millet seeds was an HSI system using short-wave near-infrared (SWNIR) bands. The wavelength range used for the HSI system was 900 nm to 1700 nm with a spectral resolution of 5 nm (N17E, Specim, Oulu, Finland). The setup for the HSI system includes a moving stage driven by a stepper motor (MRC-999-031, Middleton Spectral Vision, Middleton, WI 53562) with the InGaAs camera (Goldeye infrared camera: G-032, Allied Vision, Stradtroda, Germany) attached perpendicular to said moving stage with a single 150W halogen lamp (A20800, Schott, Southbridge, MA, USA) illuminating the stage. A computer is used for data acquisition and analysis software (FastFrame by Middleton Spectral Vision, Middleton, WI 53562).

To obtain clear images, the parameters setting included a scanning speed of 0.25 in/s, the exposure time of the camera was set to 45 ms with a framerate of 22.173 Hz, the halogen lamp angle was 54°, and the vertical distance between the lens and the sample stage was set to 12.5 cm. Samples were captured in a line scanning or pushbroom mode. The acquired hyperspectral images contained 256 wavelength bands in ".raw" format with a header file in ".hdr" format.

In the hyperspectral image acquisition, one group of 50 millet seeds would be distributed on the stage at a time and organized into rows and columns of 5 by 10. The seeds were placed to ensure that no two seeds were touching and that all the seeds were within an area that is 3x7 cm centered on the stage. Repeat this for every group of 50 seeds prepared for that day, labeling the scan correctly based on cultivar name and scan number. The seeds were placed back into the original tins, then disposed of once completed.

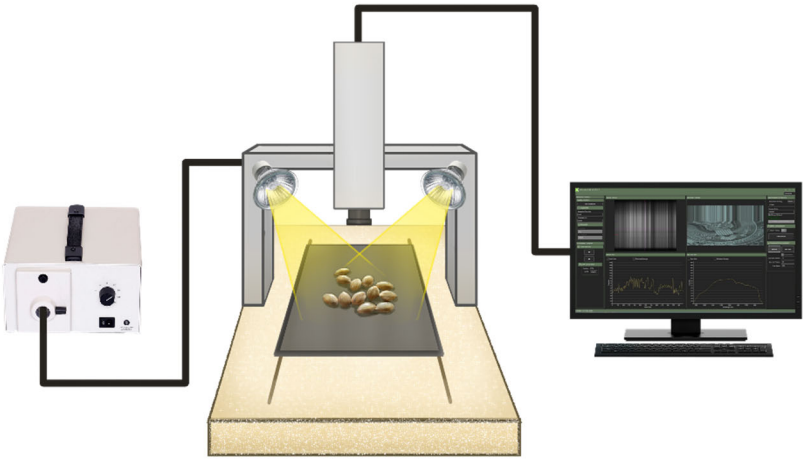

Figure 1. Hyperspectral Imaging System

To eliminate random noise from the influence of illumination and dark current of the camera, the obtained raw images needed to be corrected with the white and dark reference images. These reference images were obtained at the end of each day after the samples were scanned. The white reference images were obtained using a polytetrafluoroethylene (PTFE) Teflon plate of 99% reflectivity and 10 mm thickness placed directly on the black sample stage. The dark reference images were obtained by covering the lens of the HSI system and turning off the halogen lamp and all lights in the room. The calibration was done based on the following equation:

$$X_\lambda = \frac{I_\lambda - B}{W_\lambda - B} \quad (1)$$

In this equation, X_λ is the calibrated reflectance for the image, I_λ is the reflectance of the original radiance value for the pixel acquired by the sensor of the camera, W_λ is the reflectance of the white reference target, and B is the black reference captured while avoiding any light source in order to quantify the electronic noise of the sensor.

Data analysis

From the hyperspectral images, the seeds were segmented as the region of interest using Python (Version 3.7, Python Software Foundation, https://www.python.org/ (accessed on 15 October 2021)). To segment the ROI, two masks were used to separate each seed in the image. The first mask was to remove the background using thresholding, so all the seed boundaries in the image were clearly defined. Then, a connectivity function was used to segment each individual seed from the others in the first mask. This function counted the connected regions for each seed and fills in every seed area in the mask to a different intensity value. Next, to look at each seed individually, a second mask is created by segmenting out all values that are not equal to BW value of the seed of interest.

The spectra for each seed could then be found and analyzed. A loop was used to find each seed of interest in the image, calculating the spectra for each pixel in the seed. Then a spectrum is averaged for every pixel, calculating, displaying, and saving the mean spectra for each seed. This ROI and spectra extraction was repeated for every seed in each repetition for each type of millet. Using these mean spectra, the seeds can then be classified, and their proximate qualities determined.

The dataset of the 10 cultivars was then built for classification, using the samples as rows, and the features and labels as columns. PCA was used to compress the data and reduce the dimensionality of the hypercube. The data used a five-fold cross validation model for supervised machine learning classification. The predictor values were the PCA of the spectral data, and the dependent variables were the cultivars of millet. Different machine learning classification algorithms of SVM (Support Vector Machine), RF (Random Forest), kNN (k-Nearest Neighbors), linear discriminant analysis (LDA), and Ensemble were performed and compared for their test classification accuracies. Five models are created for each algorithm and the mean is taken of the accuracy for each algorithm.

The dataset was also built for a regression model in determining the qualities of the millet seeds. The data was collected the same as before, but instead the labels were changed to mean quality values for each seed type. Eight cultivars were used for the regression. The predictor values were still the spectral data, and now the dependent variables were the quality values. A supervised model was developed by using a five-fold cross validation model. A PLS (partial least squares) regression and a MLR (multiple linear) regression were then carried out, comparing the regression algorithms by using the values of the coefficient of determination (R^2) and mean squared error (MSE) for quality prediction accuracies. The mean of the R^2 and

MSE is taken for the five tests. This regression was repeated for each of the qualities being tested.

Results and discussion

Spectral analysis

As the data is being complied, the spectrum for each seed is first normalized for reflectance vs wavelength and cropped to both ends by 6 bands at the beginning and 15 at the end to remove noise. This isolates the region of interest for each spectrum and puts the value at a comparable position. The resulting average spectrum for each cultivar is shown in Figure 2. The spectrum for each cultivar follows a similar curve but have differing reflectance values at certain wavelengths. This could be due to the chemical and physical properties of the material at each wavelength.

The maximum absorption is found in the valleys and is seen all wavelengths around 925, 1200, 1400, and 1700. The local peaks, or minimum absorption, are around wavelengths of 1000, 1250, and 1500. The absorption values around 1400 show the first water overtones, indication the moisture content of the material being scanned. Meanwhile, the C-H bond has the third, second, and first overtone around 925, 1200, and 1700nm, respectively (Pasquini, 2003). This overtone could be an indication of the lipids in the sample. The second and first overtone for the N-H bond can be seen at wavelengths of 1000 and 1500 nm, respectively. Both wavelengths correspond with local peak values. The N-H bond could be indicating proteins within the material. Around wavelengths of 1250, the resonance of the combination of C-H bonds appears. From a glace, Minco seems to have a much smaller absorbance at both wavelengths than the other cultivars based on the higher reflectance of the spectrum. While Figure 2 shows a great visual exploring some differences, it cannot be used alone in classification. Other techniques need to be used to classify the millet cultivar clearly and accurately.

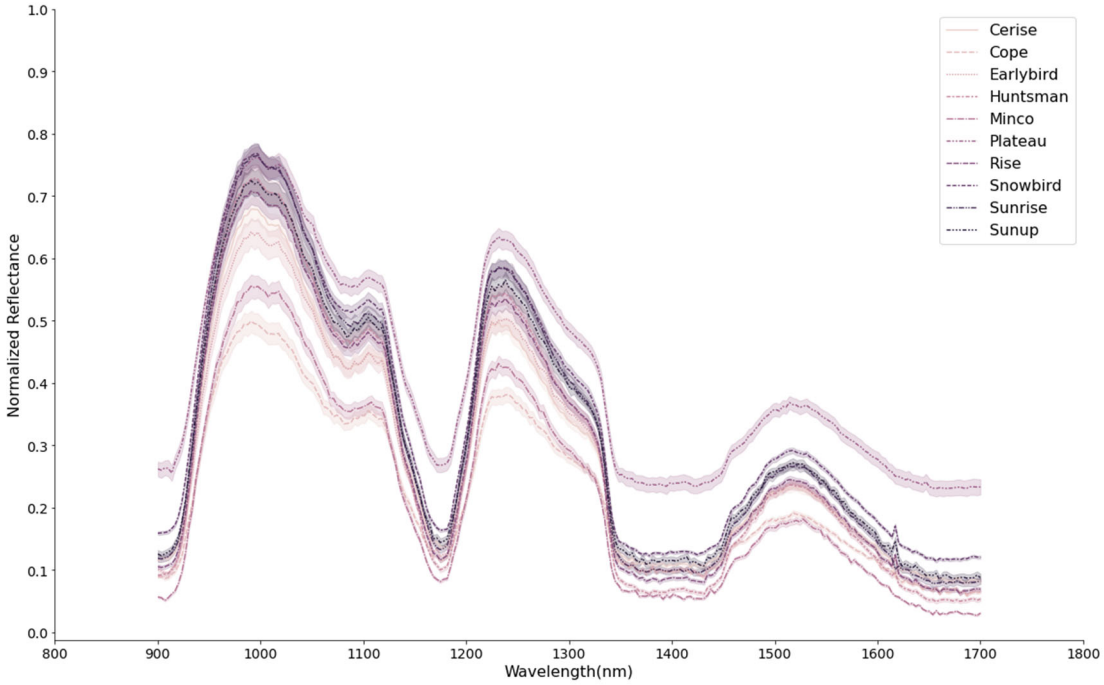

Figure 2. Mean reflectance spectra of different millet cultivar samples acquired by NIR hyperspectral imaging.

PCA and preprocessing

HSI accusation produces data that contains high dimensionality. This dimensionality creates issues in the analysis and application processes due to the complexity of the data. To better quantify the spectra for each cultivar, some preprocessing must be conducted before classification models are created. The best way to go about this is using principal component analysis (PCA). The dimensions of the spectra are reduced while retaining all details of the data using PCA. The variation in the data is captured with two PCs, with PC1 retaining 98% and PC2 with 2%. This added together covered 100% of the variability in the data. Figure 3 shows the clustering of the PCA data. Each cultivar has a stripe encompassing the variety in each cultivar. While these clusters are seemingly very distinct and separable, there is some overlap and distance between certain points. Because of these reasons, a better form of classification needs to be used.

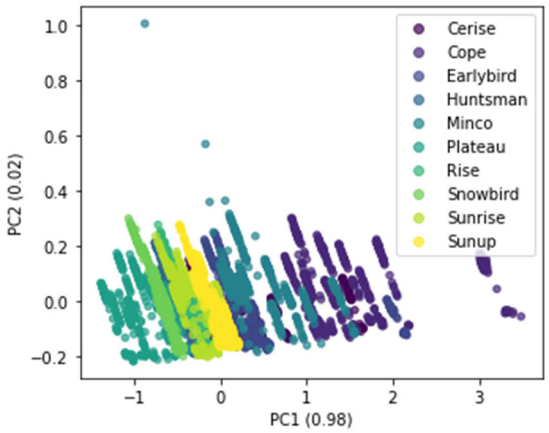

Figure 3. Principal component analysis of ten millet cultivars

Machine learning classification results

Table 1 shows the performance of different machine learning classifiers based on the mean spectra for each millet cultivar. To get the best classification rate, the raw data was analyzed and trimmed to cut off the end wavelengths and keep intact the rest of the data. The best classification result, shown in bold in Table 1, was obtained using the Gradient tree boosting classifier, with an overall test accuracy of 99.4%. The RF classifier also provided good results with an overall test accuracy of 99.1%. Both Gradient tree boosting, and RF classifiers also have a very good training set result, each with an accuracy of 100%. These results are better than X. Wang et al. (2020) who obtained an accuracy of 87.5%.

Table 1. Results of the classification of millet samples for training and test sets based on mean spectra for each cultivar.

Classifier	Total accuracy (%)	
	Training set	Testing set
SVM	70.2	71.1
RF	100	99.1
kNN	96.1	94.5
LDA	81.9	81.8
Gradient tree boosting	**100**	**99.4**

SVM: Support Vector Machine, LDA: Linear Discriminant Analysis, kNN: k-Nearest Neighbors, RF: Random Forest. Bolded line indicates the best result.

Table 2 shows the precision, recall, and F1-scores for RF and Gradient tree boosting, the two best classifiers, for each of the millet cultivars. Precision, recall, and F1-score evaluate the quality of the model, showing whether it is a good fit for the data and how well it performs. Not only is the accuracy of RF and Gradient tree boosting high, but their precision, recall, and F1-scores are also very high, with no score going below 96%. These classifiers can thus be used to classify the millet cultivars with a high dependability.

Table 2. Results of the classification of millet cultivars for test data set

Classifier	Cultivar	Precision (%)	Recall (%)	F1-score (%)
RF	Cerise	100	100	100
	Cope	100	100	100
	Earlybird	100	100	100
	Huntsman	98	99	99
	Minco	100	100	100
	Plateau	100	98	99
	Rise	99	98	99
	Snowbird	100	98	99
	Sunrise	96	98	97
	Sunup	98	100	99
Gradient tree boosting	Cerise	99	100	99
	Cope	100	100	100
	Earlybird	100	100	100
	Huntsman	99	99	99

Minco	100	100	100
Plateau	99	99	99
Rise	100	99	100
Snowbird	100	99	100
Sunrise	100	98	99
Sunup	97	100	99

In addition to PCA, another way to reduce dimensionality is selecting effective wavelengths from the spectra. Each spectrum contains so much data and information for the total amount of features and wavelengths, making it complicated to create a model without overfitting. This leads to a lot of redundancies in the spectra data for each cultivar. One way to reduce these redundancies is by looking only at the significant points in the data. This is best done by optimal wavelength selection for the mean spectra. By selecting these specific wavelengths, a reduced model using all the data in each wavelength can be determined. In this study, 5, 15, and 30 wavelengths are selected to see the number of wavelengths that makes a significant difference in the accuracy of the algorithm.

To obtain the optimal wavelengths, the dataset is used as an input for the Sequential Forward Selection (SFS) algorithm. This model uses the machine learning classifier to determine how this information is sorted. The classifier that was used was the one with the highest accuracy in Table 1, the Gradient tree Boosting model. This algorithm produces the significant wavelengths for a given number of wavelengths. These wavelengths are shown in Table 3 corresponding to the band number. These bands can then be the new dataset that the machine learning algorithm uses in testing and training. These results are shown in Table 3, resulting in a 98.00%, 98.14%, and 97.60% prediction accuracy for 30, 15, and 5 wavelengths, respectively. This table shows the highest prediction accuracy at 15 wavelengths. While still a high prediction accuracy, the feature selection made the classification accuracy slightly worse for this study.

Table 3. Results of the classification of millet cultivars based on selected wavelengths.

Classifier	No. of Features	Wavebands (nm)	Classification accuracy
Gradient tree Boosting	30	900.17, 903.53, 906.88, 910.24, 913.59, 916.95, 920.30, 923.65, 927.01, 930.36, 933.71, 937.07, 940.42, 943.77, 947.13, 950.48, 953.83, 957.18, 960.53, 963.89, 967.24, 970.59, 973.94, 977.29, 980.64, 983.99, 1004.09, 1540.94, 1673.58	98.00%
	15	900.17, 903.53, 906.88, 910.24, 913.59, 916.95, 920.30, 923.65, 927.01, 930.36, 933.71, 1004.09, 1540.94, 1673.58	98.14%
	5	900.17, 903.53, 1004.09, 1540.94, 1673.58	97.60 %

Machine learning quality prediction results

Table 4 above shows the regressions for the prediction of proximate content of the millet cultivars. To get the best regression results, the data was normalized from 0-1 and trimmed to cut off the endpoints. Both regressions gave good results with high R^2 values, specifically for the prediction of ash and carbohydrate content with R^2 values above 0.9. PLS had consistently lower error (MSE) than MLR for each quality, giving more reliable results and predictions. This is because PLS reduces the dimensionality of the data to get the best fit line, whereas MLR fits multiple and sums up the error, leading to a bigger MSE value.

Table 4. Results of the prediction of quality attributes of millet samples.

Quality	Predictive model	R^2	MSE
Ash	PLS	0.9312	0.0554
	MLR	0.9413	0.2179
Carbohydrate	PLS	0.9197	0.2331
	MLR	0.9055	0.5214
Moisture	PLS	0.8260	0.0263
	MLR	0.7764	0.1723
Crude Protein	PLS	0.7979	0.1193
	MLR	0.7476	0.3810

Crude Fat	PLS	0.8249	0.0596
	MLR	0.8335	0.2348

Conclusion

In this study the potential of using HSI in the NRI spectral range (900–1700 nm) was investigated for the classification of ten different proso millet cultivars. Additionally, the prediction of some important physicochemical attributes of proso millet, using non-destructive HSI method, was studied. Based on different classification models built from the mean spectra of each sample, the best classification performance was obtained from the Gradient tree boosting, and RF classifiers that resulted in test classification accuracies of 99.4% and 99.1%, respectively. Moreover, using PLSR for quality prediction of proso millet seeds the coefficient of determination (R^2) were obtained as 0.87, 0.80, 0.83, 0.93, and 0.92 for moisture content, crude protein, crude fat, ash, and carbohydrate, respectively. These results indicate the potential of the HSI in the NIR range as a promising tool to evaluate and classify different proso millet cultivars.

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