https://doi.org/10.17221/88/2025-RAE

Comparative study of portable Vis-NIR spectrometers for corn moisture content prediction using machine learning

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Citation: Himawan H., Alghifari M.D., Nainggolan R.J., Hermanto M.B., Nawi N.M., Omwange K.A., Al Riza D.F. (2026): Comparative study of portable Vis-NIR spectrometers for corn moisture content prediction using machine learning. Res. Agr. Eng., 72: 132–141.

Abstract: The non-destructive estimation of the corn kernel moisture content is essential for determining the optimal harvest period. Although various spectrometer sensors are currently available, their predictive performance differs due to variations in the spectral resolution and wavelength coverage. This study compared the performance of several portable spectrometer sensors with different wavelength ranges for predicting the corn moisture content. Spectral data and reference moisture content were used to develop the prediction models using partial least squares regression (PLSR) and an artificial neural network (ANN). Based on the PLSR modelling, the AS7265X and C12880MA sensors produced the best performance, with coefficients of determination (R^2) for training and testing reaching up to 0.90. Furthermore, the ANN modelling yielded improved predictive accuracy, with the highest R^2 value of 0.95 obtained using the same sensor combination. These results demonstrate that portable spectrometers show strong potential for the non-destructive field-based prediction of the corn moisture content and can serve as a reliable indicator for determining the optimal harvest timing.

Keywords: chemometrics; grain quality; non-destructive; optical sensors; spectroscopy

The quality of corn seeds is a prerequisite for improving the yield and quality of corn. The moisture content is one of the important indices for evaluating the seed quality, as it directly affects the storage time and seed germination rates. On the other hand, the moisture content is also an important factor that determines the harvest time of corn and affects the quality of corn seeds (Aswin et al. 2023). Determining the harvest time for corn seeds can be undertaken through two main approaches, namely observing the physiological characteristics of the plants and measuring

Supported by the Ministry of Education, Culture, Research, and Technology (MoECRT) of Indonesia, through grant scheme of Penelitian Fundamental – Reguler 2024 with grant master contract No. 045/E5/PG/.02.00.PL/2024 and derivative contract No. 00309.45/UN10.A0501/B/PT.01.03.2/2024.

https://doi.org/10.17221/88/2025-RAE

the moisture content of the seeds. Choosing the right harvest time is very important, as harvesting with a suboptimal moisture content – whether too high or too low – can have negative impacts. A high moisture content can cause seed quality degradation, increase the risk of fungal infections producing mycotoxins, and require higher drying costs (Martinez-Feria et al. 2019). On the other hand, an excessively low moisture content makes corn kernels brittle and prone to cracking, which can harm the harvest yield (Zhu et al. 2023). It has been reported that the optimal harvest time for corn is when the moisture content of the corn seeds is around 20–30% wet basis, depending on the corn variety (Wojcieszak et al. 2022). The right harvest time can be determined by observing signs of plant maturity, such as the drying of leaves and stems and the loss of some corn silk. With this approach, the quality of corn seeds can be maintained, resulting in an optimal product in terms of both quality and shelf life.

There are several limitations of the existing methods for measuring the corn moisture content. The commonly used methods, such as laboratory testing, require a relatively long time, involve a lot of labour, and are destructive. Additionally, other methods, such as the use of dielectric-based sensors, do allow for moisture content measurements, but they require the process of separating the corn kernels from the cob first (Nelson and Trabelsi 2012). A promising alternative is the use of commercially available optical sensor-based devices. These sensors can provide predictions of the corn moisture content with a high level of accuracy (Digman et al. 2021). However, the price of these devices is often too expensive for farmers, limiting their use in the field. Therefore, the development of technologies to measure corn moisture content in a non-destructive, inexpensive, and rapid manner has become a particular focus for farmers and the agricultural industry.

Given the advantages of non-destructive detection, including low cost, real-time results, and ease of measurement, visible/near-infrared (Vis-NIR) spectroscopy offers good application prospects in seed quality testing and plant breeding (Peiris and Dowell 2011). The spectrum obtained from Vis-NIR spectroscopy measurements can reflect information such as the internal structure and chemical composition of a material (Karoui 2018). Therefore, Vis-NIR spectroscopy technology has been considered a potential for evaluating and analysing the quality of agricultural products, such as determining the moisture content of grains (Heman and Hsieh 2016; Lin et al. 2019), orange ripeness parameters (Al Riza et al. 2023), and other quality parameters in fruits like grapes and dates (Mohammed et al. 2023; Noguera et al. 2023) or even for the soluble solids content in apples (Tran and Fukuzawa 2020).

In recent years, the development and application of portable spectrometers and spectroscopy-based instruments have progressed rapidly, with various trials conducted in the agriculture and food sectors (Tran and Fukuzawa 2020; Noguera et al. 2023). This development is a positive step, enabling the translation of laboratory (benchtop) spectrometer capabilities into more compact, portable, and affordable detection systems without sacrificing the performance equivalent to conventional spectrometers. Furthermore, this development allows for the design of in-situ detection systems, which reduces the need for sample transportation to laboratories, thereby increasing the efficiency and speed of analysis.

In general, portable spectrometers tend to have lower resolution and a more limited wavelength range compared to benchtop spectrometers (Teixeira Dos Santos et al. 2013). Therefore, researchers and practitioners still need to evaluate the extent to which portable spectrometers can be relied upon as measurement instruments. Although various studies have demonstrated the effectiveness of spectroscopy in detecting moisture content in grains, the use of portable spectrometers in this context is still relatively minimal. Considering the potential of spectroscopy in the Vis-NIR range and the availability of portable spectrometers, this study aims to explore the capabilities of portable Vis-NIR spectrometers in predicting the corn moisture content. Based on the obtained spectra, partial least square regression (PLSR) and artificial neural network (ANN) models were developed using machine learning. The predicted moisture content results from the models built using portable spectrometers will be compared to determine which portable spectrometer has the potential for further development.

MATERIAL AND METHODS

Sample preparation. This study was conducted using corn cultivated individually in Malang City, Indonesia. A total of 300 seeds of the NK 7207 hy-

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brid variety (Syngenta) were planted as the initial cultivation material, selected due to their resistance to leaf blight and stem rot. Corn harvesting was initiated at 120 days after planting (DAP) and subsequently conducted at 3-day intervals, namely at 120, 124, 128, 132, 136, 140, 144, 148, 152, and 158 DAP, following the physiological development stages of the crop. At each harvesting stage, 25 corn samples were collected and used for the spectral data acquisition and reference analysis. Spectral measurements were performed once for each sample at every harvest stage. Consequently, a total of 250 spectral datasets were obtained, which were used for the subsequent data processing and model development.

Design of the instrument and spectral acquisition. Three spectrometer-based sensors with complementary spectral ranges were employed to capture reflectance information related to the physicochemical properties of corn seeds, and their key specifications are summarised in Table 1. The AS7265X sensor (SparkFun Electronics, USA) covers the visible to near-infrared (Vis-NIR) region (410–940 nm), which is sensitive to pigment-related absorption and structural scattering. The C12880MA mini-spectrometer (Hamamatsu Photonics, Japan) operates across the ultraviolet, visible, and short-wave near-infrared regions (312–882 nm), where spectral information is still dominated by surface characteristics and weak overtone scattering rather than strong water absorption features. The AS7421 sensor (ams OSRAM, Austria) covers the near-infrared region (750–1 050 nm), which is strongly associated with O-H overtone absorption bands related to the moisture content. The combination of these sensors was intended to provide complementary spectral information across the UV, VIS, and NIR regions to enhance the moisture content prediction accuracy.

Spectral data acquisition was performed using a pre-designed detection system. This system is affixed to the corn kernels (Figure 1), and a trigger button is pressed to start scanning. Light from the detection system is absorbed and reflected by the sample, and the reflected light is read by the sensor and converted into spectral data. Each wavelength generates a value or data point. The detection system is integrated with Bluetooth, allowing transmission of the readings to a laptop via Bluetooth. The readings can then be viewed in the Serial Monitor section of the Arduino IDE on the laptop. Additionally, the AS7421 sensor is integrated with software installed on the laptop, so the readings can be displayed within the software itself.

Determination of the moisture content. The moisture content was determined using the oven-drying method in accordance with the Indonesian National Standard SNI 6944:2015. Each corn seed sample (approximately 5 g) was weighed using an analytical balance with an accuracy of 0.0001 g and placed in an 8 cm diameter cup. Samples were dried at 130 °C for 4 hours. The drying duration was selected based on a preliminary experiment conducted prior to the main study, which confirmed that a constant mass was achieved after 4 hours of drying under the same temperature and sample conditions. After drying, the samples were cooled in a desiccator for 30 minutes before weighing to determine the moisture loss.

Table 1. Comparison of the spectrometer specifications

Sensor	Wavelength range (nm)	Spectral resolution/ channels	Measurement mode	Dominant spectral information	Relevance to moisture content prediction
AS7265X (SparkFun)	410–940	18 discrete channels (Vis–NIR)	reflectance	pigment absorption, surface scattering, structural information	indirectly related to moisture via scattering changes and kernel structure
C12880MA (Hamamatsu)	312–882	288 channels (UV-Vis-short NIR)	reflectance	short-wavelength absorption and surface characteristics	supports detection of early-stage surface and compositional changes
AS7421 (ams OSRAM)	750–1 050	64 channels	reflectance	O-H overtone absorption bands	directly sensitive to water content in biological materials

Vis-NIR – visible/near-infrared

https://doi.org/10.17221/88/2025-RAE

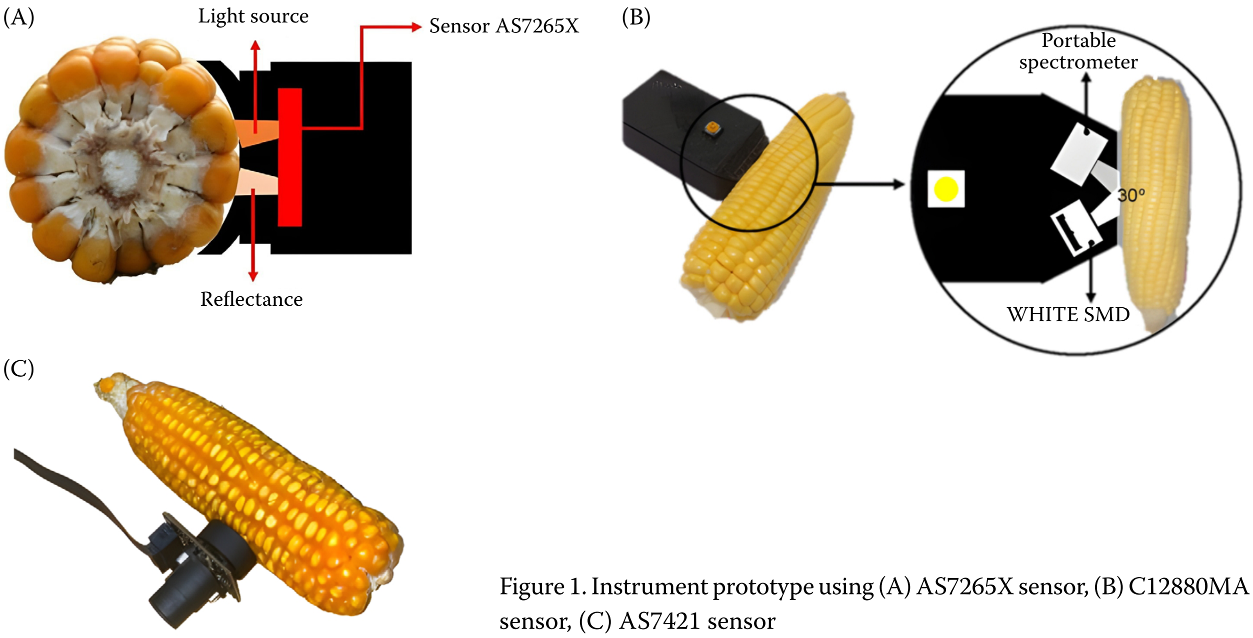

Figure 1. Instrument prototype using (A) AS7265X sensor, (B) C12880MA sensor, (C) AS7421 sensor

The moisture content in a wet basis of each seed was calculated according to Equation (1).

$$M = (m_0 - m_1)/(m_0 - m) \times 100\% \quad (1)$$

where: M –the moisture content on a wet basis (%); m_0 – the mass of the cup and sample before drying (g), m_1 – the mass of the cup and sample after drying (g); m – the mass of the empty cup (g).

Spectral data processing methods. The correction of the sample spectral data with a white reference is necessary to ensure accurate measurement results that truly reflect the original characteristics of the sample. This process helps eliminate the influence of various external factors, such as fluctuations in the light source intensity, detector sensitivity, or reflectance of the measuring device, so that the results obtained are more consistent and reliable, thus, the spectral data correction used Equation (2).

$$R = \frac{Is}{Iw} \times 100\% \quad (2)$$

where: R –the corrected reflectance intensity (%); Is – the reflectance intensity of the sample; Iw – the reflectance intensity of the white reference.

The datasets applied in the model are of three types: all features, pre-processing, and selected features. All features use all the reflectance spectra. The pre-processing datasets used in this study are: (*i*) moving average (MA) with 3 window sizes, (*ii*) multiplicative scatter correction (MSC), and standard normal variance (SNV). The dataset used was obtained from the datasets of the four previous sensors, and feature selection was performed using the principal component analysis (PCA) method to select several wavelengths that have the most influence on the target data, namely the corn moisture content. Feature selection was performed using a threshold loading score value. Table 2 shows the percentage variance of the relative reflectance data. It takes three principal components (PCs) to achieve more than 80% of the cumulative variance in the relative reflectance data, while, in the relative reflectance data from AS7421 sensor, the first PCs achieve 97% of the variance, and the relative reflectance data from sensors AS7265X and C12880MA only need three PCs to represent 85% of the variance.

Modelling method. This research used the Python 3.10.12 programming language in Google

Table 2. Percentage of variance from the three sensors

Sensor type	PC			Total
	1	2	3	
AS7265X	71	16	5	92
C12880MA	55	23	12	90
AS7421	97	2	1	100

PC – principal component

https://doi.org/10.17221/88/2025-RAE

Collaboratory to build the model. The total number of datasets used is 250 datasets. Furthermore, the data is divided into training data (80%) and testing data (20%). The division of the training and testing data uses the train_split_data function, and the random_state function makes the randomisation process deterministic in the python library. The regression model was built using PLSR. The cross-validation method is used to provide a more accurate and stable estimate of the model performance using limited data more efficiently. ANN modelling is also used, hyperparameter optimisation uses a technique called random grid search, which samples a range of values for important parameters such as the number of layers, hidden nodes, activation function, and learning rate. The activation function used in the hyperparameter configuration is a rectified linear unit (ReLU). The ANN architecture uses a learning rate of 0.001 and 1 000 epochs. The best model for predicting the moisture content of corn seed cobs is determined based on metric evaluation such as the *R*-square (R^2) of the training and testing, root mean square error (RMSE), and ratio of performance to deviation (RPD).

RESULTS AND DISCUSSION

Statistic on the moisture content of corn. This study involved 250 samples of the corn variety NK 7207. The moisture content of the samples was measured using gravimetric methods between October 22 and November 27, 2023, when the corn was 3–4 months old. During this period, the moisture content of the corn dropped from 85.66% to 28%, reaching the optimal level for seed harvesting. It should be noted that this study only used samples of the corn variety NK 7207. The box plot of the moisture content can be seen in Figure 2.

Figure 2 shows the decrease in the corn moisture content during drying under direct sunlight. Other factors that affect the drying rate are the environmental conditions such as the air temperature, humidity, and wind speed. Drying will occur faster in dry and windy air. Changes in the moisture content during harvest have a significant impact on the physical and chemical properties of corn. Physically, corn undergoes changes in weight, volume, hardness, and colour. The mass of the corn kernel changes as the moisture content decreases, and the corn becomes harder. At a high moisture content, the physical structure of the corn weakens, and its colour changes from yellow to orange. Chemically, changes in the corn moisture content affect the levels of amylose, amylopectin, protein, fat, vitamins, and minerals. As the amylose and amylopectin levels change, the protein and fat decrease, and the vitamins and minerals decrease (Karakelle et al. 2020; Córdova-Noboa et al. 2021). Overall, changes in the physical and chemical properties of corn during drying improve its quality. Corn with a low moisture content is more durable, more resistant to pests and diseases, and has a higher nutritional value.

Characteristics of the corn spectra. Figure 3 shows the Vis-NIR reflectance spectra obtained from the three sensors. All the samples have similar spectrum trendlines, where low reflectance means high absorbance. Figures 3A and 3B show that there is a significant absorbance peak at around 400–500 nm, this is consistent with the research conducted by Zhang and Guo (2020) which may be related to the Soret absorption. The visible spec-

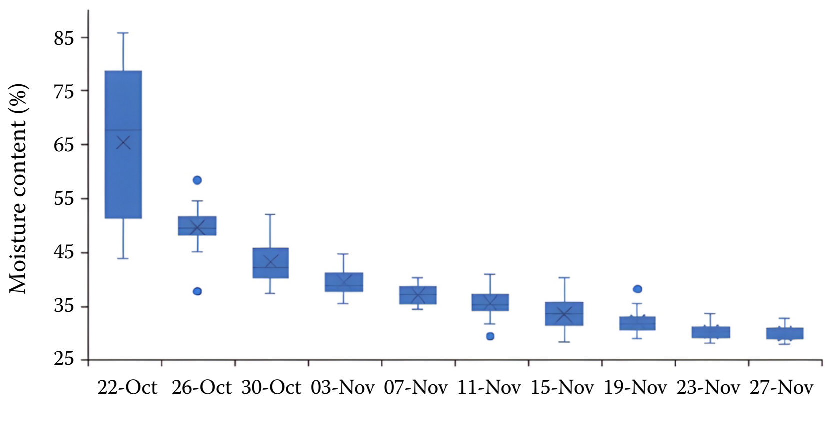

Figure 2. Box plot of the moisture content (%)

https://doi.org/10.17221/88/2025-RAE

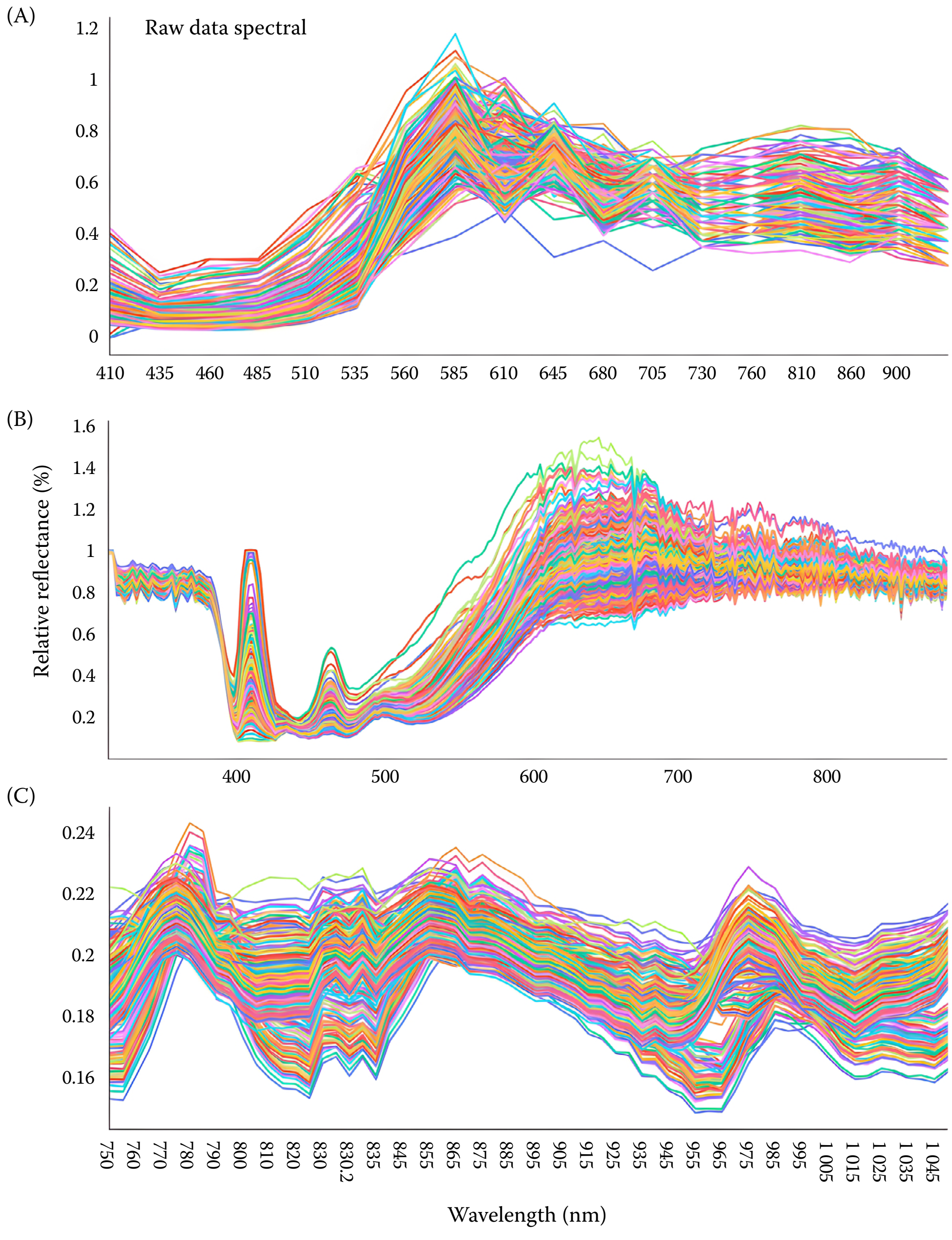

Figure 3. Corn spectra of the (A) AS7265X sensor, (B) C12800MA sensor, (C) AS7421 sensor

troscopy directly correlates with the colour change experienced by the corn kernels (Karoui 2018). The colour of corn kernels comes from natural pigments such as carotenoids. As the moisture content decreases, these pigments may undergo changes in concentration, degradation, or oxidation. It is proven that the absorption of carotenoid pigments is in the wavelength range of 400–500 nm (Ashenafi et al. 2023). Figure 3C shows the absorbed intensity of the sample at 970 nm. According to Heman and Hsieh (2016), the absorbance at around 970 nm can be attributed to the combined effect of the second O-H overtone of carbohydrates and water. The absorbance at about 1 200 nm can be attributed to the C-H stretching of the second overtone of the carbohydrates. The absorption at about 1 450 nm is mainly due to the absorption band of water associated with the O-H stretching first overtone.

https://doi.org/10.17221/88/2025-RAE

PLSR modelling results. Table 3 shows the performance of partial least square regression (PLSR) models for various sensor types based on the Vis-NIR spectrum. The spectral dataset used is the result of the pre-processing data such as MA, MA + MSC, MA + SNV, and selected features. PLSR modelling using the 10-fold cross-validation method is used to optimise the resulting accuracy. In addition, selecting the optimal number of latent variables is an important step in building a robust PLSR model. The proper determination helps prevent the risk of overfitting, where the model is too complex and only suitable for training data, as well as underfitting, where the model is too simple and fails to capture important patterns in the data.

The best PLSR model selection is based on the evaluation metrics listed in Table 2. In the PLSR model generated from the AS7265X sensor, the best model is obtained using the selected feature dataset with R^2 train (0.91), R^2 test (0.89), RMSE train (3.39), and RMSE test (3.67). Although the pre-processed dataset achieved an R^2 train of 0.93, the raw dataset had the largest RPD test value (3.01). Wavelength selection using the PCA technique based on loading scores identified key wavelengths at 460, 510, 535, 560, 585, 645, 705, 760, and 810 nm. Several studies have also reported that wavelength feature selection is helpful to extract more useful information from the full spectrum and to improve the prediction performance (Abu-Khalaf and Hmidat 2020). Then, the best PLSR model generated from the C12880MA sensor is obtained from the MA + MSC dataset with R^2 train (0.89), R^2 test (0.90), RMSE train (3.76), and RMSE test (3.53). The resulting RPD value is more than 3, this indicates that the model built is very good to apply (Cao et al. 2024). Furthermore, the best PLSR model generated from the AS7421 sensor was obtained from the raw dataset with R^2 train (0.90), R^2 test (0.87), RMSE train (3.57), RMSE test (3.94), and RPD (2.80). Several studies reported that Vis-NIR spectroscopy has the potential to be applied to evaluate the quality of agricultural products, such as predicting the rice moisture content (Heman and Hsieh 2016), predicting the moisture content in red meat (Kamruzzaman et al. 2022), and predicting the moisture content in red peppers (Lim et al. 2014).

Currently, various studies have reported methods for determining the moisture content of agricultural products. However, most of these studies used bench-top spectroscopy. For example, Heman and Hsieh (2016) predicted the moisture content of rice

Table 3. Performance comparison of three sensor types for the corn moisture content prediction using PLSR modelling

Type of sensor	Dataset	R^2 train	R^2 test	RMSE train (%)	RMSE test (%)	RPD
AS7265x	Raw data	0.92	0.88	3.30	3.89	2.84
	MA	0.93	0.86	3.11	4.17	2.65
	MA + MSC	0.93	0.87	3.02	3.93	2.81
	MA + SNV	0.93	0.87	3.03	3.92	2.82
	Selected features	0.91	0.89	3.39	3.67	3.01
C12880MA	Raw data	0.88	0.84	4.06	3.96	2.50
	MA	0.90	0.88	3.60	3.84	2.87
	MA + MSC	0.89	0.90	3.76	3.53	3.12
	MA + SNV	0.90	0.88	3.53	4.54	2.86
	Selected features	0.80	0.78	5.13	5.46	2.11
AS7421	Raw data	0.90	0.87	3.57	3.94	2.80
	MA	0.89	0.86	3.86	4.09	2.70
	MA + MSC	0.84	0.80	4.58	4.93	2.24
	MA + SNV	0.89	0.86	3.86	4.09	2.70
	Selected features	0.83	0.82	4.41	5.85	2.36

PLSR – partial least squares regression; RMSE – root mean square error; RPD – ratio of performance to deviation; MA – moving average; MSC – multiplicative scatter correction; SNV – standard normal variance; RPD values < 1.5 indicate poor prediction, whereas values > 2.5 indicate good to excellent predictive performance

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using the Foss NIR Systems 6500 technology; Rabanera et al. (2021) predicted the moisture content in peanuts; and Solar and Solar (2016) predicted the moisture content in hazelnuts. The prediction models in these studies achieved an R^2 value of 0.9, indicating a high level of accuracy, consistent with the bench-top spectroscopy-based approaches. This finding is supported by Zhang and Guo (2020), who reported an R^2 value of 0.9 for predicting corn kernel moisture content across different varieties using Vis-NIR spectroscopy (375–1 100 nm). This research indicates that portable spectrometer-based prediction models have a great potential for practical application.

ANN modelling results. ANN has several parameters that greatly affect the resulting model. The choice of ANN model structure is critical for achieving optimal model performance, as the input, hidden, and output layers are interconnected and jointly influence the modelling process. The input used in this network is the number of spectrum variables generated from each sensor. The AS7265X sensor has 18 input variables; 288 variables from the C12880MA sensor; and 64 variables from the AS7421 sensor. The model building uses a multilayer perceptron (MLP), which is an artificial neural network consisting of one input layer, one or more hidden layers, and one output layer. In this study, the determination of the number of hidden layers and nodes for each hidden layer uses the GridSearchCV technique. The hyperparameters used are the learning rate = 0.001 and epoch = 1 000.

The best model was determined based on the ability to achieve the highest R^2 value, which is close to 1, indicating that 100% of variable *X* in this study, the spectrum with all the features and selected features can explain variable *Y*, which, in the context of this study, is the moisture content of corn cobs. This study compared the performance of three portable spectrometers to predict the quality of corn cobs (Table 4). The best prediction model for the AS7265X sensor used the dataset with all features, with R^2 values of 0.95 for training and 0.88 for testing, and an ANN structure of 20–10. This model had an RPD value of 2.87, indicating an excellent moisture content prediction capability. The C12880MA sensor also showed good prediction performance, with R^2 values of 0.92 for training and 0.90 for testing, and an RPD value of 3.14. Meanwhile, the AS7421 sensor showed low performance with R^2 values of 0.37 for training and 0.36 for testing. The number of hidden layers and nodes in the ANN was optimised for each sensor based on the data complexity, amount of data, and desired accuracy level. This study used the rectified linear unit (ReLU) activation function for the hidden layer.

Based on the evaluation of the prediction models that have been developed using the three sensors, the AS7265X and C12880MA sensors show great potential for further development. The AS7265X sensor has a lower resolution when compared to the C12880 sensor, however, in terms of cost, the AS7265X sensor has a significant advantage with a manufacturing cost of approximately $180, compared to the C12880MA sensor which requires a manufacturing cost of up to $600. Therefore, in accordance with the objectives of this research, the AS7265X sensor was chosen to be developed as a more economical and efficient tool. The AS7265X sensor has been widely researched and developed as an instrument for agricultural product evaluation. For example, Noguera et al. (2023) developed an AS7265X-based instrument to measure the ripeness level of grapes through the soluble solid content (SSC) and titratable acidity (TA) parameters. The study demon-

Table 4. Performance comparison of three sensor types for the corn moisture content prediction using ANN modelling

Type of sensor	Dataset	ANN structure	R^2 train	R^2 test	RMSE train (%)	RMSE test (%)	RPD
AS7265x	all feature	20-10	0.95	0.88	2.79	3.14	2.87
	selected feature	20-10	0.91	0.87	3.54	3.25	2.78
C12880MA	all feature	100-50	0.92	0.90	3.46	2.88	3.14
	selected feature	100-50	0.82	0.77	4.97	5.35	2.07
AS7421	all feature	100-100	0.37	0.36	9.42	7.21	1.25
	selected	100-100	0.26	0.28	10.27	7.66	1.18

ANN – artificial neural network; RMSE – root mean square error; RPD – ratio of performance to deviation

https://doi.org/10.17221/88/2025-RAE

strated promising predictive performance, with a model accuracy reflected by an R^2 value of 0.8. In addition, Mohammed et al. (2023) revealed the AS7265X sensor's ability to predict quality parameters as well as estimate the shelf life of fresh dates, reinforcing the potential of this sensor for wide applications in agriculture.

CONCLUSION

The performance of the three sensors has been evaluated in predicting the corn moisture content. In the development of prediction models using PLSR, all three sensors – AS7265X, C12880MA, and AS7421 – showed equivalent prediction capabilities. Meanwhile, the modelling using ANN resulted in the optimal performance for the AS7265X sensor with a two-hidden layer model (10-20) and the C12880MA sensor with an ANN structure (100-50), learning rate (0.001), and number of epochs (1 000). Based on the evaluation of the prediction model, the AS7265X and C12880MA sensors have the potential to be further developed. The AS7265X sensor has a lower manufacturing cost compared to the C12880MA sensor. Therefore, the AS7265X sensor has the potential to be implemented as a low-cost portable spectrometer-based device to perform nondestructive measurements of agricultural products.

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Received: June 12, 2025
Accepted: February 19, 2026
Published online: June 17, 2026