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Integration of Portable NIRS Spectroscopy with the Internet of Things (IoT) for a Rice Quality Monitoring System in Storage Warehouses

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Abstract: Rapid and non-destructive monitoring of rice quality during storage is essential for supporting effective warehouse management. This study aims to develop and evaluate the integration of Portable Near-Infrared Spectroscopy (NIRS) with an Internet of Things (IoT) framework for real-time rice quality monitoring. A quantitative experimental approach was employed by acquiring NIRS spectra in the wavelength range of 740–1070 nm from fresh and aged rice samples. The spectral data were automatically transmitted via the IoT system to a centralized server for storage and analysis. Rice quality parameters, including moisture, fat, and protein content, were predicted using a Partial Least Squares Regression (PLS-R) model based on raw spectra without spectral pretreatment. The results indicate that the PLS-R model achieved good predictive performance for moisture and fat content, with validation correlation coefficients (R) ranging from 0.87 to 1.00 and Residual Predictive Deviation (RPD) values of 1.11–3.65 for moisture and 3.70–4.65 for fat in both fresh and aged rice samples. In contrast, protein prediction showed limited accuracy, particularly in fresh rice samples with an RPD value of 1.79. The IoT system primarily functioned as a real-time data acquisition and transmission platform, enabling integrated rice quality monitoring. Overall, the findings confirm that NIRS–IoT integration is feasible for monitoring rice quality based on moisture and fat content during storage.

Keywords: Internet of Things (IoT); PLS regression; Portable near-infrared spectroscopy; Real-time monitoring; Rice quality

Introduction

In modern agricultural industry, accurate and efficient product quality monitoring is a crucial aspect in ensuring food safety and the economic value of products, particularly in rice commodities. Portable Near-Infrared Reflectance Spectroscopy (NIRS) technology has shown rapid progress in its application for monitoring rice quality in storage warehouses. The working principle of NIRS, based on light absorption and reflection, enables real-time analysis of product chemical parameters, providing a quick and non-destructive assessment method (Liu et al., 2021).

NIRS' ability to determine important parameters such as Free Fatty Acids (FFA) content in rice has been effectively demonstrated, allowing timely interventions to maintain quality during storage (Du et al., 2022). The development of chemometric techniques combined with NIRS further strengthens the precision and accuracy of quality predictions, making it a practical solution compared to conventional laboratory methods that require time and complex sample preparation (Badaró et al., 2021; Xu et al., 2019). This portable NIRS device is especially relevant for warehouse operators who require quick and efficient analysis on-site at product storage locations.

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However, the implementation of this technology is not without its main challenges. The accuracy of NIRS greatly depends on a robust calibration model, which is influenced by the variation in food matrices. The diverse environmental conditions of warehouses complicate the development of stable calibrations (Rego et al., 2020b). On the other hand, integrating NIRS devices with Internet of Things (IoT) technology offers a common solution in the form of real-time data access, enabling continuous monitoring of rice quality parameters and rapid decision-making (Li et al., 2023).

Specifically, the integration of portable NIRS technology with IoT provides several tangible advantages such as predictive analysis, where machine learning algorithms can analyze data directly to identify trends and predict quality issues before significant damage occurs (Parrenin et al., 2024). The implementation of IoT monitoring systems can also increase transparency in the supply chain, strengthening consumer trust in the food products produced (Badaró et al., 2021; Rossi & Lozano, 2020). However, technical challenges such as interoperability between IoT devices, data security, and the relatively high initial implementation costs remain obstacles that need to be addressed to fully harness the potential of this integration for widespread use (Entrenas et al., 2019; Tian et al., 2024). This situation represents a gap that requires further research to ensure optimal technology implementation that is accessible to both small and large businesses.

Previous studies have shown that various spectral preprocessing methods such as Partial Least Squares Regression (PLS-R) method, combined with portable NIRS technology, can accurately detect the authenticity of Ciherang rice varieties, with a correlation coefficient of up to 0.99, emphasizing the great potential of this technology for rapid and effective field applications (Ito et al., 2019).

Based on this gap, this study aims to develop the integration of portable NIRS spectroscopy techniques with IoT to create a real-time rice quality monitoring system in storage warehouses. The novelty of this study lies in the application of the NIRS and IoT combination, supported by advanced machine learning algorithms, for accurate prediction of rice quality parameters. The scope of this research includes testing system accuracy, optimizing data preprocessing methods, and evaluating the effectiveness of system implementation in varied storage environments.

Method

Time and Place

The research activity started from July to December 2025, and the study has been conducted at the Integrated Laboratory at the University of Nusantara Technology and at the MBRIO Food Laboratory for chemical content analysis.

Research Method

The method used to assess the authenticity of Ciherang rice involves the use of the SCIO Portable Near Infrared Reflectance Spectrometer technology. This instrument is capable of accurately projecting the chemical composition in rice, thanks to its ability to identify O-H, C-H, and C-O groups. The Portable Near Infrared Reflectance Spectrometer system is equipped with software that can build predictive models using statistical and multivariate mathematical data, along with data pre-treatment as described by (Lan et al., 2020) The detection of the purity level of Ciherang rice using the Portable Near Infrared Reflectance Spectrometer is rarely employed at present, thus there is a need to increase analyses for detecting the purity level of Ciherang rice and its integration with IoT (Du et al., 2022; Nagel-Held et al., 2023).

Sample Preparation

SCIO is a portable NIRS device used in this study. Prior to use, the device undergoes a calibration process to ensure that the measurement conditions align with the specified standards, preventing errors or the storage of measurements that could affect product quality, and ensuring the validity of the results. The spectrum sampling is performed by directing the portable NIRS device at each sample, with three repetitions conducted at wavelengths ranging from 740 to 1070 nm. The collected spectral data is automatically stored in the cloud server and made available for download for further analysis. To analyze the spectral data, The Unscrambler X 10.4 software, equipped with a pre-treatment feature, is used. This feature helps eliminate potential issues caused by radiation scattering from the sample and ensures that the data remains consistent, while preserving the essential information needed for accurate predictions (Birenboim et al., 2021; Cortés et al., 2019a).

Calibration Model Evaluation and Validation

This study employs the Partial Least Squares Regression (PLS-R) technique for analysis, which is a linear approach in data processing (Agulheiro-Santos et al., 2022; Genisheva et al., 2018; A. Purwanto & Sudargini, 2021) stated that the PLS-R method is effective in identifying key components by utilizing the largest variation from both spectral and destructive data simultaneously. This method can also compress data into several important variables and predict the percentage of rice purity using a regression line based on calibration data. The amount of data used in the Partial

Least Squares method reaches 45 data points, with a division of 30 data for calibration and 15 data for validation. This data division aims to achieve the development of a more optimal model (Ana & Sitohang, 2024; Ni et al., 2024; Rady et al., 2020). The performance of the developed model is evaluated based on parameters used in the PLS-R method, such as the correlation coefficient (r), standard error (SE), coefficient of variation (CV), residual predictive deviation (RPD), and consistency (Entrenas et al., 2019; Sun et al., 2022).

In general, this research procedure is conducted in four stages: rice sample preparation, spectrum data collection of rice using a portable near-infrared spectrometer, development of the Ciherang rice authenticity prediction model, and model testing, as shown in Figure 1.

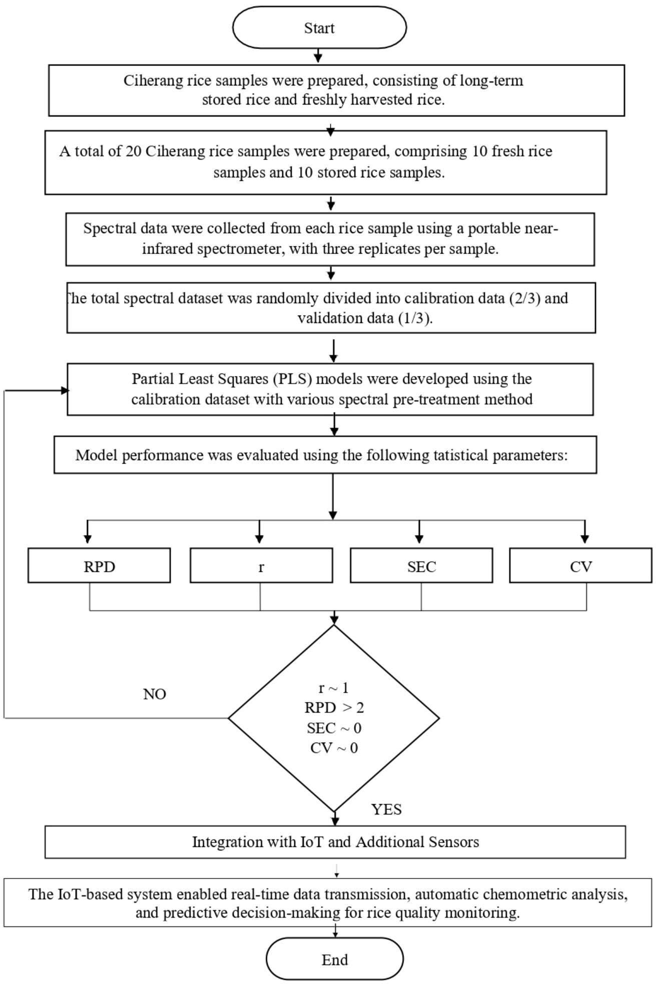


Figure 1. Research procedure flowchart illustrating the four stages: rice sample preparation, spectrum data collection, model development for Ciherang rice authenticity, and model testing

Data Transformation

The spectral data obtained from measurements using the portable near-infrared spectrometer with a wavelength range of 740-1070 nm can be in the form of reflectance or transmittance values of the material (Burns and Ciurczak, 2008). This spectrum is then transformed into absorbance by converting the reflectance values using Equation 1. This transformation is carried out because the chemical composition of a material has a linear relationship with absorbance data (Mohsenin, 1984)

$$\text{Absorbance} = \log\frac{1}{\text{R}} \quad (1)$$

where:
A = absorbance (unitless)
R = reflectance (unitless)
log = base-10 logarithm

Calibration and Validation Results Evaluation

According to Ozaki et al., (2007) the spectra produced by NIR instruments contain information about a material, but this information is not directly obtained due to overlapping data and baseline fluctuations. Multivariate data analysis is required to address these issues, one of which is Partial Least Squares (PLS). PLS is a relatively new approach to linear regression and algorithms. This method is particularly suitable for calibration with a small number of samples by combining experimental results, namely chemical data and NIRS data (Puleo et al., 2022).

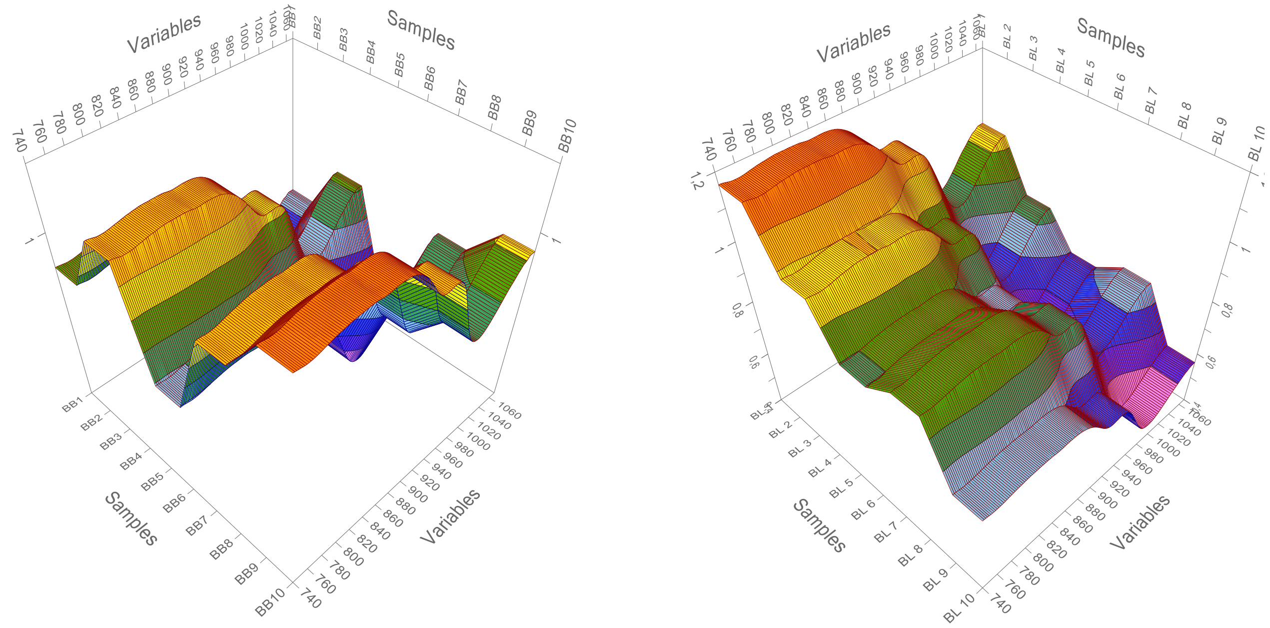
The samples used consisted of 10 new rice samples and 10 old rice samples. The measured data on the NirCal software was divided into 2/3 for the calibration set and 1/3 for the validation set. Calibration is the first step, aimed at determining the correlation between the chemical content obtained from destructive laboratory testing and the transflective portable near-infrared spectrometer (Zhou et al., 2021) . Validation is carried out after obtaining the calibration regression model. The purpose of validation is to test and ensure that the NIR calibration is accurate and can be used as a testing tool (Isdhiyanti et al., 2024; Sringarm et al., 2024).

The calibration and validation models are evaluated using statistical parameters such as bias, correlation coefficient (r), Standard Error of Calibration (SEC), Standard Error of Prediction (SEP), Coefficient of Variation (CV), and Residual Predictive Deviation (RPD) (Y. A. Purwanto et al., 2013).

Result and Discussion

NIRS Spectrum Characteristics of Rice Samples

Figure 2 shows a matrix plot of the raw NIRS spectra of new rice samples and old rice samples within the wavelength range of 740–1070 nm. Each spectral curve represents the reflectance response of each rice sample measured using a portable NIRS instrument. The spectral patterns exhibit differences in intensity and curve shape between new and old rice. The spectrum of new rice shows a more pronounced intensity variation, particularly in the wavelength region associated with O–H and C–H bonds. This indicates a relatively higher moisture content and a more stable chemical structure (Entrenas et al., 2019; Rego et al., 2020a). In contrast, the spectrum of old rice tends to be more homogeneous and flatter, reflecting physical and chemical changes during storage, such as a decrease in moisture content and lipid oxidation. These spectral characteristic differences indicate that the raw NIRS spectrum contains sufficient chemical information to distinguish rice condition based on storage duration, making it suitable for direct input into PLS modeling without spectral pretreatment.



(a) (b)

Figure 2. Matrix plot of the spectra generated from (a) new rice and (b) old rice

PLS-R Model Performance

Table 1 presents the calibration and validation results of the Partial Least Squares Regression (PLS-R) model without spectral pretreatment for predicting the chemical content in old rice samples.

The moisture content parameter shows calibration (R = 0.93) and validation (R = 0.87) correlation coefficients, which are considered good. However, the RPD value of 1.11 indicates that the predictive ability of the model is still in the "adequate" category, making it more suitable for initial estimation rather than precise quantitative predictions. In the fat content parameter, the model demonstrates excellent performance with a calibration R value of 0.98 and a validation R value of 1.00. The RPD value of 3.70 indicates that the model has reliable predictive ability and can be used for quantitative analysis. This suggests that fat content changes due to storage can be well detected by the raw NIRS spectrum. Meanwhile, the protein parameter in old rice shows the best performance compared to other parameters, with an RPD value of 4.95 and a validation R of 0.98. These results indicate that the variation in protein content in old rice is relatively larger, making it easier to model using the PLS approach without spectral pretreatment.

Table 2 presents the results of the PLS-R modelling without spectral pretreatment on new rice samples. The moisture content parameter shows excellent performance with calibration and validation R values of 0.98, and CV values of 0.01. The very high RPD value of 3.65 indicates that the model has strong and stable predictive ability. This highlights the high sensitivity of the NIRS spectrum to moisture content through O–H bonds. The fat content parameter also shows good performance with a calibration R value of 0.89 and a validation R value of 0.94, along with an RPD value of 4.65. These results indicate that the raw NIRS spectrum can accurately represent variations in fat content without requiring additional pretreatment.

In contrast, the protein parameter shows good performance, with an RPD value of 1.79 and a high coefficient of variation (CV) of 2.40. While the calibration and validation R values are still considered good, the low RPD value indicates that the model is not yet able to predict protein content reliably. This is likely due to the low variation in protein content in new rice and the overlap of protein absorption bands with water and carbohydrate bands in the NIRS spectrum.

Table 1. Results of data analysis on old rice samples using PLS

Chemical Content	Calibration R	SEC (%)	SEP (%)	CV (%)	RPD	Consistency (%)	Validation R
Moisture content	0.93	0.08	0.05	0.37	1.11	160.68	0.87
Fat content	0.98	0.02	0.01	1.01	3.70	160.91	1.00
Protein	0.99	0.04	0.03	0.48	4.95	122.61	0.98

Table 2. Results of data analysis on new rice samples using PLS

Chemical Content	Calibration R	SEC (%)	SEP (%)	CV (%)	RPD	Consistency (%)	Validation R
Moisture content	0.98	0.00	0.00	0.01	3.65	108.28	1.00
Fat content	0.89	0.00	0.00	1.24	4.65	129.71	0.94
Protein	0.98	0.07	0.04	2.40	1.79	139.88	0.91

Implications for IoT-Based Rice Quality Monitoring System

Figure 3 shows the workflow of the integration system between Portable NIRS and the Internet of Things (IoT) developed for monitoring rice quality in storage warehouses.

The system workflow begins with the spectral data acquisition process, followed by data transmission, data processing, and presentation of rice quality information to the user. The first stage is the NIRS spectrum measurement, where the portable NIRS is used to scan rice samples directly without destructive treatment. This process generates raw spectral data within the wavelength range of 740–1070 nm, which represents the chemical characteristics of the rice. The second stage is IoT-based data transmission, where the spectral data from the measurements is automatically sent via the internet to a cloud server (Hao et al., 2019; Prananto et al., 2021). This process enables centralized data storage and eliminates the dependence on manual data transfer. The third stage is data processing and quality prediction, where the raw spectral data is analyzed using the Partial Least Squares Regression (PLS-R) model without spectral pretreatment. This model converts the spectral data into predicted values for rice quality parameters such as moisture content, fat content, and protein. The final stage is the presentation of monitoring results, where the prediction outcomes are displayed as digital information that can be accessed by warehouse operators in real-time. This workflow emphasizes that the NIRS–IoT integration enables rice quality monitoring to be carried out quickly, automatically, and continuously.

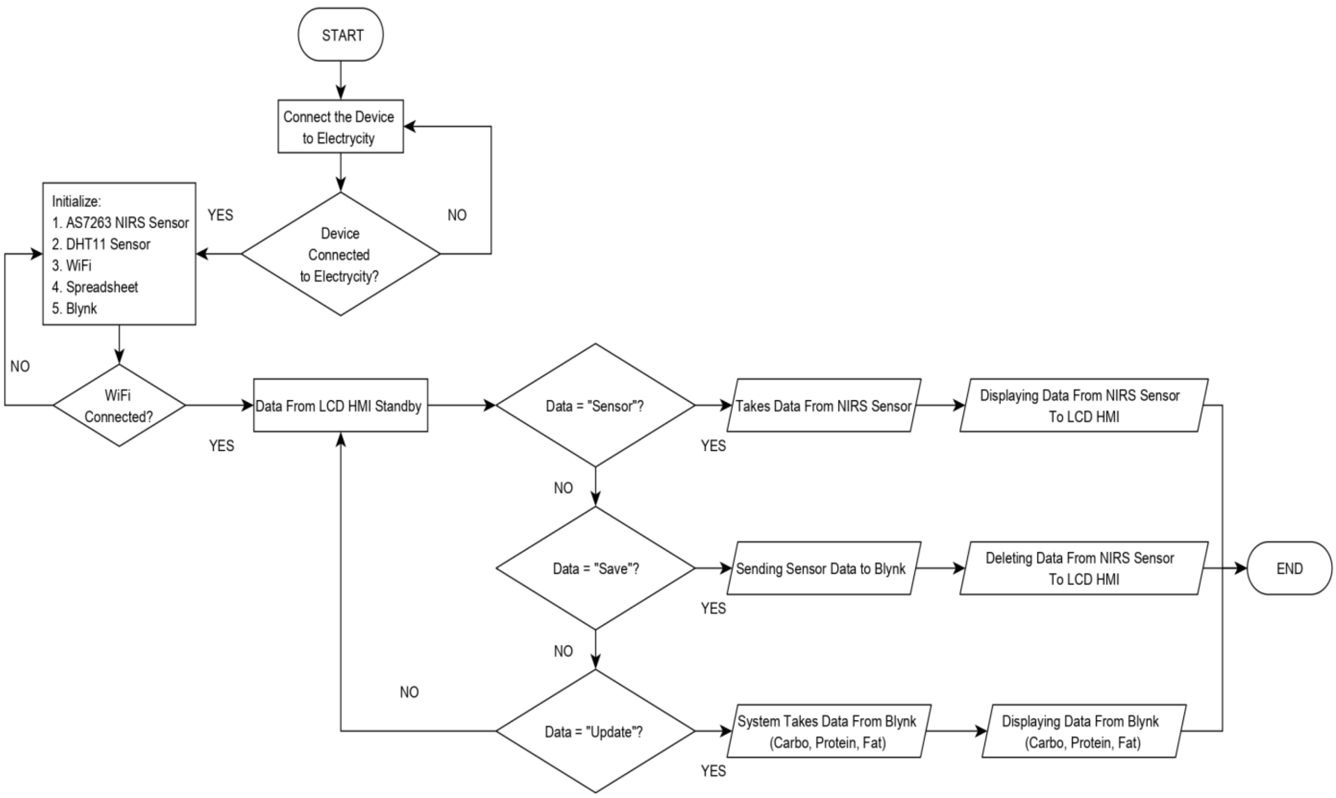


Figure 3. Workflow of the integration of portable NIRS spectroscopy with the Internet of Things (IoT) system

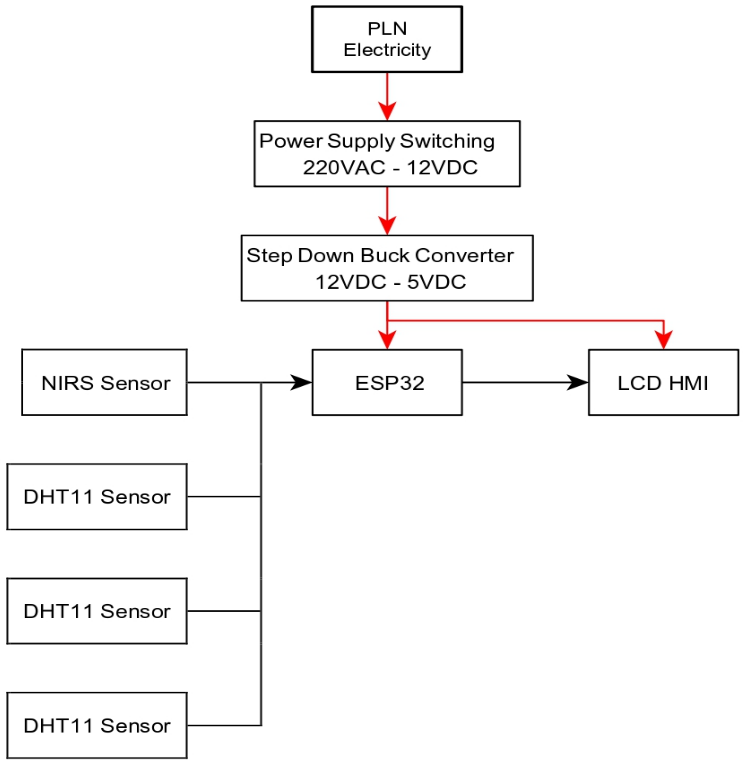


Figure 4. Illustrates the structure and interrelationships between the system components

The rice quality monitoring system based on the integration of Portable NIRS and IoT, designed in this study, is structured with a layered architecture to ensure efficiency, scalability, and ease of system development. The first layer is the sensor layer, consisting of portable NIRS as the spectral data acquisition device. In this layer, direct interaction between the instrument and the rice sample generates raw spectral data, which forms the basis for quality analysis. The second layer is the communication layer, which connects the NIRS device to the cloud system via the IoT network (Feng et al., 2024; Rego et al., 2020a). This layer ensures that spectral data can be transmitted in real-time, securely, and continuously from the warehouse location to the central server. The third layer is the data processing layer, where spectral data is analyzed using the PLS-R model without spectral pretreatment. In this stage, the spectral data is processed into quantitative information that reflects rice quality based on key nutritional parameters. The fourth layer is the application layer, which displays the analysis results in the form of a monitoring dashboard. This dashboard allows users to track changes in rice quality, compare new and old rice conditions, and support decision-making related to storage management. The system architecture in Figure 3 shows that the integration of NIRS and IoT not only functions as a measurement system but also as an intelligent monitoring platform that supports data transparency, operational efficiency, and sustainable rice quality management (Chen et al., 2023; Cortés et al., 2019b).

Conclusion

This study demonstrates that the integration of Portable Near-Infrared Spectroscopy (NIRS) within the 740–1070 nm range with an Internet of Things (IoT) system enables automated, non-destructive, and real-time monitoring of rice quality during storage, as summarized in the abstract. Based on the results of data analysis using the Partial Least Squares Regression (PLS-R) model, moisture and fat content exhibited good predictive performance, with validation correlation coefficients (R) ranging from 0.87 to 1.00 and Residual Predictive Deviation (RPD) values of 1.11–3.65 for moisture content and 3.70–4.65 for fat content in both fresh and aged rice samples, indicating predictive capability from acceptable to good levels. In contrast, protein content showed limited predictive performance, particularly in fresh rice samples with an RPD value of 1.79, indicating that the model is not yet reliable for quantitative protein prediction. The final PLS-R model was developed using raw spectra without spectral pretreatment (Chun et al., 2025; Genisheva et al., 2018). The IoT system in this study functioned as a real-time data acquisition and transmission infrastructure to a centralized server, enabling integrated storage and immediate access to prediction results, without claims of improved spectral prediction accuracy. Overall, the findings confirm that NIRS–IoT integration is feasible for monitoring rice quality based on moisture and fat content in storage warehouses, while highlighting limitations in protein prediction that should be addressed in future research.

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Author Contributions
Conceptualization, methodology, investigation, software, visualization, project administration, A.P.A.; formal analysis, validation, D.R.M., M.R.A., and M.M.; Resources, M.R.A.; data curation, supervision, A.P.A., D.R.M., and M.M.; writing—preparation of original draft, writing—reviewing and editing, A.P.A., M.R.A., and M.M. All authors have read and approved the published version of the manuscript.

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Conflicts of Interest
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of any affiliated institutions or organizations.

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