

1           **A Portable IoT NIR Spectroscopic System to Analyze**  
2                           **the Quality of Dairy Farm Forage**

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12   **Abstract**

13   Having rapid and reliable knowledge of the quality of dairy farm forage is crucial for technicians  
14   and producers. However, the necessary equipment to fulfil these requirements is oftentimes  
15   expensive and complex to use. This work presents a portable instrument system to analyze the  
16   nutritional values of dairy farm forage using near-infrared spectrometry (NIRS) techniques. Using  
17   the Internet of Things (IoT) tools, data are sent to the cloud for processing; following this, they  
18   are accessible to any device. To analyze the nutritional values of dairy farm forage a chemometric  
19   model and implemented the instrument to understand the relationship between the measured  
20   spectrum and the concentration of the substances of interest was developed. The quality of the  
21   proposed methodology was validated by comparing reference and NIR data by using the statistic  
22   Standard Error of Calibration.

23  
24   **Keywords**

25   Food quality, NIRS, spectroscopy, chemometrics, Internet of Things (IoT), cloud computing.

## 27 **1. Introduction**

28 Possessing quick and reliable knowledge of the nutritive values of dairy farm forage is  
29 crucial for technicians and producers. Most instrumental techniques employed for quality  
30 evaluation are time-intensive, expensive, and involve a considerable amount of manual work.  
31 There is growing interest in developing simpler and faster instrumental devices for determining  
32 the physical and chemical characteristics in agricultural system samples. In spectroscopic  
33 analysis, an alternative for raw sample analysis is near-infrared spectroscopy (NIRS), which has  
34 taken its place among other proven spectroscopic tools for determining the chemical and physical  
35 properties of foods. The NIRS absorption originated from the overtones of CH, NH, OH, and SH  
36 stretching vibrations and from stretching–bending combinations involving these groups. The  
37 near-infrared spectrum is located between the infrared and visible spectrum, from 2500 nm to 800  
38 nm ( $4000\text{--}12500\text{ cm}^{-1}$ ) (Ozaki et al., 2007; Williams et al., 2001), and the spectral signal can be  
39 used for advanced analytics. However, this technology traditionally has been reserved as an  
40 expensive laboratory instrument for experts. Because of the numerous publications that support  
41 the efficacy of analytical applications that use NIRS for the quantification of quality and safety  
42 parameters in agri-food (Decruyenaere et al., 2009; Baeten et al., 2008; De la Haba et al., 2007;  
43 Fernández Pierna et al., 2006; Okparanma et al., 2013; Volkers et al., 2003; Hermida et al., 2005),  
44 researchers are working on developing new portable NIRS instruments.

45 Related to feed analysis, numerous authors have reported using NIRS to conduct rapid  
46 analysis of feed nutritional quality (Nie et al. 2008; Huang et al. 2008; van Barneveld et al. 2018).  
47 NIRS holds real potential for routine on-site analyses, for example at the point of feed delivery or  
48 for use in stock feed manufacturing (Yan et al., 2018).

49 The NIRS researcher, user, and engineer must give special attention to sample presentation  
50 devices that directly govern the quality of spectra themselves. There is a technique available for  
51 any type of liquid, slurry, powdered or solid sample. Radiation interacting with a sample may be  
52 absorbed, transmitted, or reflected. For raw forage analysis, the solid sample is used as a diffuse  
53 reflectance because most of the incident radiation is reflected. In this mode, the incident radiation

54 illuminates perpendicularly to the sample surface. Normally, the incident radiation cannot reach  
55 a deeper position in a sample because of high absorption or multiple scattering (Ozaki et al.,  
56 2007).

57 NIR spectra contain a lot of physical and chemical molecule information. However, this  
58 information cannot always be extracted straightforwardly from the spectra because the NIR  
59 spectra consists of a number of bands arising from overtones and combination modes that overlap  
60 heavily with one another. Additionally, multicollinearity is quite strong in this region; therefore,  
61 powerful chemometric techniques are essential for allowing reliable extraction of relevant  
62 information hidden in the NIR spectral data. Chemometrics covers all methods of multivariable  
63 calibration, including spectral data preprocessing, and calibration model development for  
64 qualitative and quantitative analyses.

65 Advances in NIR spectroscopy have made this technology one of the most efficient tools for  
66 determining feed nutritive parameters. Based on the type of detector, the portable NIRS can be an  
67 array detector or single-detector instrument. Comparing both detectors, the price for a single one  
68 is lower and thus reduces the hardware costs. These reasons have facilitated the development of  
69 instruments with single detectors (Olakunle et al., 2018). Besides the price and portability of the  
70 miniaturized NIRS systems to carry out on-site and in-field measurements, there is another  
71 problem to solve, one related to data transference and management. Existing NIRS instruments  
72 cannot extract the spectra data easily because they do not usually have the appropriate  
73 connectivity. This causes a problem when it comes to following the evolution of the data. This  
74 information can be useful for technicians, producers, or administration responsible for food  
75 quality and safety. Having data history is always an added benefit that can provide valuable  
76 information about what is happening on the farm or factory. In this sense, advances in  
77 communication technologies and smartphones open a range of new possibilities that could be  
78 applied to develop a solution fitting the desired conditions. Thus, Olakunle et al. discussed in  
79 detail the benefits and challenges of Internet of Things (IoT) technologies and data analytics in  
80 agriculture. Liu et al. (Liu et al., 2019) developed and implemented a modern agriculture IoT

81 system for the cloud, whereas Crocombe (Crocombe, 2018) provided detailed information about  
82 the technologies used in portable/miniaturized spectroscopy, discussing their applications and  
83 emerging fields. A review of recent smartphone spectroscopy systems is provided in (Rateni et  
84 al., 2017).

85 In summary, the main contributions of this work are the following:

- 86 • From a NIR evaluation module, a high-performance portable NIR spectrometer was  
87 developed.
- 88 • A chemometric model into the instrument to extract relevant information about forage  
89 quality was implemented.
- 90 • IoT capability were included in the developed NIR spectrometer to process and  
91 communicate data everywhere and all the time, with different devices with access to the  
92 Internet.

93 The remainder of this paper is organized as follows: Section II presents the materials used in  
94 this work. Section III describes the implementation of the IoT NIR measurement system. Section  
95 IV is devoted to the chemometrics analysis. Cloud computing is addressed in section V. Finally,  
96 Section VI contains the conclusion.

97

## 98 **2. Materials**

99 Generally, an NIRS system comprises four components: light source, light-isolating  
100 mechanisms, detector, and sampling device (Wang et al. 2007). Most of the instruments utilize  
101 tungsten filament halogen lamps as the light source. This is because they are an effective  
102 compromise between performance and cost. This type of lamp is particularly suitable for use in  
103 low voltage settings. The light source must be close to the sample to light it up with strong intensity.  
104 The employed technology for the wavelengths selection greatly influences the performance of the  
105 instrument.

106           Regarding portable applications in food sector instruments equipped with a diffraction grating  
107 and an array detector, the Si-diode array or InGaAs-diode array have seen increased use due to  
108 their compact size, versatility, robustness, and low cost. Fig. 1 shows the spectrometer approach  
109 proposed by Texas Instruments (TI) (Texas Instruments, 2016). The light source is first collimated  
110 and then sent to the diffraction grating to split into different wavelengths. The focusing mirror  
111 collects the diffracted radiation and sends it to a digital mirror array (DMD) instead of an array  
112 detector. The DMD consists of an array of hundreds of thousands of micromirrors.

113           However, when activating or not activating the mirror columns, only the desired wavelengths  
114 are reflected by the detector. This programmable architecture allows the use of a high-performance,  
115 cost-effective single element detector—for example a photonic device based on InGaAs. This  
116 approach has a small form factor suited for field analysis, which provides mechanical stability. In  
117 this work, the TI NIRscan Nano evaluation module is used (Texas Instruments, 2017) (see Fig.  
118 2a). It is a compact battery-operated evaluation module for portable NIRS solutions. It supports  
119 Bluetooth Low Energy (BLE) to enable mobile measurements for hand-held spectrometers. This  
120 module operates by illuminating the test sample at an angle so that specular reflections are not  
121 collected. At the same time, it gathers and focuses diffuse reflections through the slit. The  
122 embedded processor commands the DMD controller turn on only the precise mirrors, which are  
123 illuminated by the specific light wavelengths to be measured at each instant of time. The easy  
124 programmability of the processor allows users to command specific column widths or other  
125 patterns for their spectroscopy requirements to achieve high signal-to-noise ratio values. This  
126 architecture enables adaptive scanning techniques, which are not possible with array detectors—  
127 for example, chemometric methods with multiple patterns to look for physical and chemical  
128 substances. A microcontroller board (LOLIN D32) is attached over the spectrometer module (see  
129 Fig. 2b) to control the servomotor (MG90S) that moves the sample holder. A DC-DC converter  
130 (Pololu U1V10F5) is used to convert the 3.7 V from the battery to 5 V to power the servomotor.

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132

### 133 **3. IoT Measurement System**

134 Fig. 3 shows the general scheme of the proposed measurement system. It consists of the  
135 NIRscan Nano module and a microcontroller board based on the well-known ESP32 module,  
136 which is responsible for turning the servomotor (M) where the sample holder is placed. The  
137 spectrometer will make several measurements when the sample holder is rotating, which ensures  
138 the measurements are as homogeneous as possible. These data can be sent to a mobile application  
139 via Bluetooth, which is integrated into the NIRscan. There is also the option of sending them to  
140 the computer via a USB connection.

141 Due to the limitation of storage and computing capability of the local system on chip, some  
142 researchers use a limited chemometrics model for portable spectra instruments. However, in the  
143 proposed instrument, spectra data are sent to the cloud, where, with the rapid progress of IoT and  
144 cloud computing, along with the development of machine-learning algorithms, real-time  
145 applications can be guaranteed. Once the model or models are deployed on the cloud, there is no  
146 limitation on storage or computing capability. In addition, the results are accessible from other  
147 mobile devices with Internet access.

148 The small size of the sample window (10 mm x 10 mm) makes it difficult to obtain  
149 reproducible spectra analyzing raw samples with a particle size larger than the instrument sample  
150 window when measuring them directly. To avoid this drawback, a semi-circular sample holder  
151 was attached to the spectrometer, as shown in Fig. 4. This holder rotates and, in each position, 10  
152 measurements are made. The microcontroller board has two buttons, one to start the  
153 measurements and another to set the load position of the sample holder.

154 When the start button is pressed, the servomotor begins to turn, stopping at different positions  
155 where the measurements are made. In this research work, it was optimized the number of positions  
156 to be scanned per sample going from 5 to 20 positions. The best results were obtained when  
157 scanning 10 points per sample. Once the sample holder reaches the 180° position, it returns to the  
158 initial position, where it waits to make a new measurement. When the load button is pressed, the

159 servomotor goes to an intermediate position of about 90°, facilitating the loading and unloading  
160 of the sample. When the device is not performing either of these two actions, the microcontroller  
161 will go into sleep mode to minimize power consumption. The movement of the alfalfa inside the  
162 holder does not affect the measure because the quantity of alfalfa that is introduced, is large  
163 enough so that the movement of it inside the sample holder is minimal. What is sought when  
164 performing the 10 measurements is to obtain the most homogeneous results possible in the  
165 sample, so that even if it moved, it would not affect the result since the exact measurement points  
166 are not really important, but the important thing is to cover the largest sample area.

167       Autonomy is fundamental in any portable IoT device. In this work a 3.7 V, 1800 mAh  
168 Lithium polymer battery is used to power the system, providing an estimated autonomy of 15  
169 hours when it is at rest. A 10 kΩ NTC thermistor is required to safely charge the battery and  
170 monitor its temperature. When the measurement is being made, the spectrometer alone consumes  
171 500 mA, but the measurement time is only about 16 s. Therefore, if the user makes an average of  
172 10 measurements per hour, the autonomy of the prototype will be 12 hours (if it is on all the time).  
173 Texas Instruments provides free software and firmware downloads to give developers flexibility  
174 and advanced control of the spectrometer.

175

#### 176 **4. Chemometric Analysis**

177       Chemometrics are a wide range of statistical and mathematical methods for extracting useful  
178 information from the NIR spectra. These methods use a multivariable calibration in which the  
179 wide spectrum is considered to establish a relationship between spectra data and analytical  
180 parameter quantification. Fig. 5 shows the process to develop the chemometric model for the  
181 quantification of nutritive forage value.

##### 182 *A. Sample Selection*

183       The first task of this process is the selection of the sample group for calibration, which must  
184 be well defined statistically, including a wide variability of the type of samples. In this work, 90  
185 samples were collected from different farms in Asturias Province (north Spain) during 2018–2019

186 and analyzed using the NIRS designed instrument and reference procedures. For reference data,  
 187 we performed the chemical analysis using traditional analytical methodologies: Crude Protein  
 188 (CP) through Kjeldahl analysis, Neutral Detergent Fiber (NDF), and Acid Detergent Fiber (ADF)  
 189 through Van Soest analysis (Van Soest et al., 1991). Table 1 provides the range, mean, and  
 190 standard deviation of the reference analysis. As can be seen, it was observed a wide variability  
 191 when determining fiber parameters (Standard deviation >5) due to different maturity stages of the  
 192 plant; however, it was noted a lower standard deviation for the crude protein parameter. The  
 193 protein content of alfalfa as cut varies according to the cut and vegetative stage of the crop and  
 194 the leaf content after the drying procedure.

195 **Table 1.** Statistic for Nutritive Value of Alfalfa Samples ( $N = 90$ )

Analytical Methodologies	Range (%)	Mean	Standard Deviation
CP	7.19 – 17.27	14.49	1.61
ADF	20.15 – 39.24	29.22	4.00
NDF	29.24 – 60.44	39.36	5.40

196 CP: Crude Protein; ADF: Acid Detergent Fibre; NDF: Neutral Detergent Fibre.  
 197

198  
 199 *B. Spectral Acquisition*

200 To scan a sample, a scan configuration must be created. Two scan configurations come  
 201 preloaded in factory settings: “Column” and “Hadamard.” Column selects one wavelength at a  
 202 time. The Hadamard scan creates a set with several wavelengths multiplexed at a time and then  
 203 decodes the individual wavelengths. Fig. 6 displays the spectrum plot and the scan configuration  
 204 parameters. A scan can be divided into 1–5 sections, being configured in each section: the method  
 205 (Column or Hadamard), spectral range (start and end wavelength), digital resolution (wavelength  
 206 points captured into the defined spectral range), exposure time (between 0.635 – 60.960 ms) and  
 207 the number of scans per sample (in this work, 10 scans in 10 different points of the sample).

208 The NIR spectrum contains information about the major X-H chemical bonds in an  
 209 agricultural product such as lucerne. The spectrum is dependent on all the functional groups that



210 absorb NIR radiation, and this information has important implications in agricultural products due  
211 to the relationship between NIR vibration bands of functional groups and nutritional parameters.  
212 Moreover, the reference bands related to crude protein are associated to N-H vibrations in the  
213 spectra regions around 1470, 1500 to 1530 and 1640 to 1680 nm.

214 For the major fiber components, the tentative bands assignments are associated to structures  
215 of cellulose, pectins and lignin, with absorbance at 1170, 1420 and 1490nm. Lucerne spectra  
216 collected with the developed device are shown in Fig. 7 (Burns and Ciurczak, 2008).

### 217 *C. Spectral Preprocessing*

218 An important effect related to analysing intact samples by NIR is the particle size, being  
219 desirable to try to eliminate or reduce it, using a variety of mathematical approaches for spectra  
220 preprocessing. The aim of this step is to improve the signal-to-noise ratio, removing the redundant  
221 information contained in the spectra. There are several methods for preprocessing spectra data,  
222 such as averaging all the individual spectra collected for one sample or using smoothing or  
223 derivative procedures. The first one consists of performing a median of all the measures. The result  
224 is a single spectrum of each sample with a reduced thermal noise. Another effect to be minimized  
225 is scattering: in NIRS, the reflected energy is a mixture of diffuse and specular reflections, which  
226 are dependent on the scattering nature and absorption characteristics of the sample (Bertrand et  
227 al. 2000). This makes the baseline/intensity of each sample vary, introducing challenges when  
228 making a model. To solve this issue, transformations such as the multiplicative scatter correction  
229 (Barnes et al. 1989) and the standard normal variate correction (SNV) (aes et al., 2004) are  
230 common in NIRS chemometrics. In this work, the SNV was applied to each spectrum individually  
231 and calculated the mean and standard deviation of each point. To calculate the SNV spectra, the  
232 average at that point ( $\mu$ ) is subtracted from each point and divided by the standard deviation ( $\sigma$ ).  
233 The correction can be seen in Figs. 7 and 8.

234 To improve the quality of the spectra, a Savitzky–Golay filter was used. This is a low-pass  
235 filter which applies least squares smoothing to reduce noise while maintaining the shape and  
236 height of waveform peaks, which is why it is widely used in spectrometry. In this work, a window

237 size of 19, a polynomial of order 3, and a derivative of order 2 were used. The result of the  
238 pretreatment can be seen in Fig. 9. In addition, to improve model results, the wavelengths that do  
239 not provide information from the model were analyzed and removed.

240 When applying SNV and Detrend on spectra population (Fig. 7), the effects of particle size  
241 are compensated and shift of the base line is removed or minimized (see Fig. 8).

242

#### 243 *D. Calibration Model*

244 The next step after preprocessing is the calibration of the model. It consists of obtaining a  
245 correlation between the reference method and the spectral data. The most widely used regression  
246 methods in NIRS are multiple linear regression (Martens et al. 1989), principal components  
247 regression, and partial least squares regression (PLSR) (Wold et al., 2001). This last method can  
248 improve the precision of the model parameters with the increase in number of relevant variables  
249 and observations, and it is widely used in NIRS calibration developments. To attempt this work,  
250 a PLSR model has been employed using all the data included in the spectra. To select the best  
251 equations, the following statistics have been considered: standard error of calibration (*SEC*) and  
252 determination coefficient of calibration ( $R^2_C$ ). The first one ( $R^2_C$ ) establishes a correlation between  
253 the analytical data obtained in the laboratory and those predicted by the calibration ( $R^2_C$ ).  
254 Mathematically,

$$255 \quad R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (1)$$

256 where  $n$  is the number of samples used in the calibration,  $y_i$  refers to the reference values,  $\hat{y}_i$  is  
257 the value predicted by the model, and  $\bar{y}$  is the average reference value.

258 The second parameter is calculated using the formula:

$$259 \quad SEC = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^M (y_i - \hat{y}_i)^2} \quad (2)$$

260 where  $\hat{y}_i$  and  $y_i$  are the predicted and measured values for sample  $i^{\text{th}}$ . This value provides the  
 261 averages of expected typical uncertainty for the prediction of future samples.

262 Table 2 shows the best statistics of chemometric models for predicting nutritive values in  
 263 alfalfa samples. These characteristics were selected according to the lowest standard error of  
 264 calibration and the lowest error of prediction. As can be seen, when increasing variability in  
 265 calibration, population  $R^2_c$  is increased. For CP with a lower variability ( $SD = 1.61$ ), the  $R^2_c$  is  
 266 0.516. To evaluate the statistical data of developed models, this work focused on the *SEC* and the  
 267 ability of being useful to farms for feeding management.

268 The standard errors in the developed models were obtained according to Commission  
 269 Regulation (EU) 2017/2279 of 11 December 2017 amending Annexes II, IV, VI, VII, and VIII to  
 270 Regulation (EC) No 767/2009 of the European Parliament and to the ISO 13906 and 16472 related  
 271 to these nutritive parameters.

272 **Table 2.** Statistics of Chemometric Models to Predict Nutritive Parameters of Alfalfa Samples

Analytical Methodologies	$R^2_c$	SEC
CP	0.516	2.11
ADF	0.742	3.96
NDF	0.704	8.03

273

274 CP: Crude Protein; ADF: Acid Detergent Fibre; NDF: Neutral Detergent Fibre;  $R^2_c$ :  
 275 Determination coefficient for calibration; SEC: Standard Error of Calibration; RPD: Standard  
 276 deviation/SEC.

277

## 278 5. Cloud Computing

279 According to the schema in Fig. 5, after performing the measurement, the spectrometer sends  
 280 the data in the “csv” format to the computer via BLE. Once there, the spectra data is sent to the  
 281 cloud, where the statistical treatment presented in Section IV was carried out. Using the Python  
 282 language, a dashboard to display the data and allow users to upload and download the spectra was  
 283 developed.

284 The provider used to host the application is Amazon Web Services. Fig. 10 shows the  
285 dashboard structure on the cloud. To facilitate its deployment in other platforms, the developed  
286 application runs inside a Docker container. The user, using a web browser, where the dashboard is  
287 displayed, communicates with the cloud through the free and open source software, Nginx. This  
288 works as a web server and allows users to communicate with the application itself, giving the  
289 system a layer so that the data are not directly exposed. After that, a Python WSGI HTTP Server  
290 for UNIX (Gunicorn) is found. The developed application utilizes this software. The application was  
291 developed using Dash, which is a framework for building analytical web applications. The data  
292 spectra are stored in a database, a nonrelational and open source database called MongoDB.

293 Finally, the pre-processed spectra data (see C. Spectral Preprocessing section) are displayed  
294 in a dashboard where the user can see the results and the graphics generated, as can be seen in Fig.  
295 11. Deploying the entire system in the cloud allows us to adapt new volumes of data in the future  
296 with relative ease. It is possible also to do so in such a way that any authorized person can access it  
297 from anywhere in the world if they have access to the Internet and not depend on the construction  
298 and maintenance of their own servers, which makes a very low initial cost.

299

## 300 **6. Conclusion**

301 This work utilizes an affordable IoT portable NIRS system to analyze the nutritional  
302 parameters of dairy farm forage. This system can be useful for the owners or technicians  
303 responsible for the nutritional state of animals in farms. The proposed instrumentation allows  
304 users to evaluate the quality of the forage, increase sampling without incurring a cost, obtain  
305 results in real time, and make it possible to make quick decisions, avoiding delays related to  
306 carrying samples from the farm to the laboratory. Moreover, specialized training is not required  
307 for users of this instrument. Thanks to the storage and processing in the cloud, the data are  
308 accessible from any site with Internet access, facilitating the visualization and use of the data for  
309 making decisions. The potential offered by cloud computing suggests this system would be useful  
310 not only for agriculture monitoring but also for environmental and biomedical sensing.

311

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317

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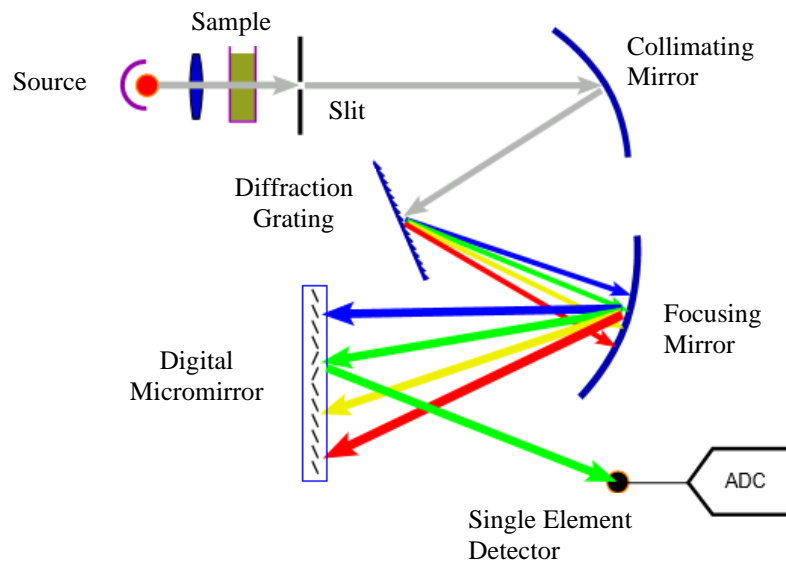
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388 **FIGURES**

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391 **Fig. 1.** Spectrometer using a micromirror array and a single element detector.

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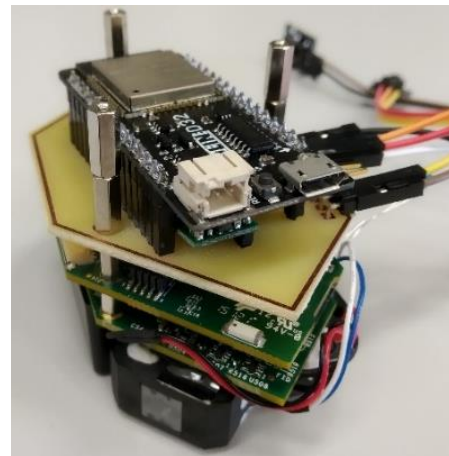
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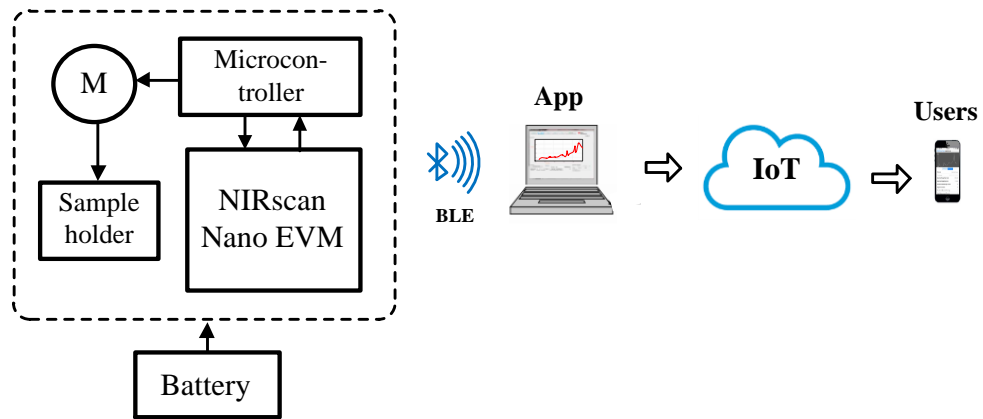
b)

402 **Fig. 2.** (a) NIRscan Nano module and (b) Microcontroller board places over NIRscan module.

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405 **Fig. 3.** General scheme of the proposed measurement system (M = servomotor).

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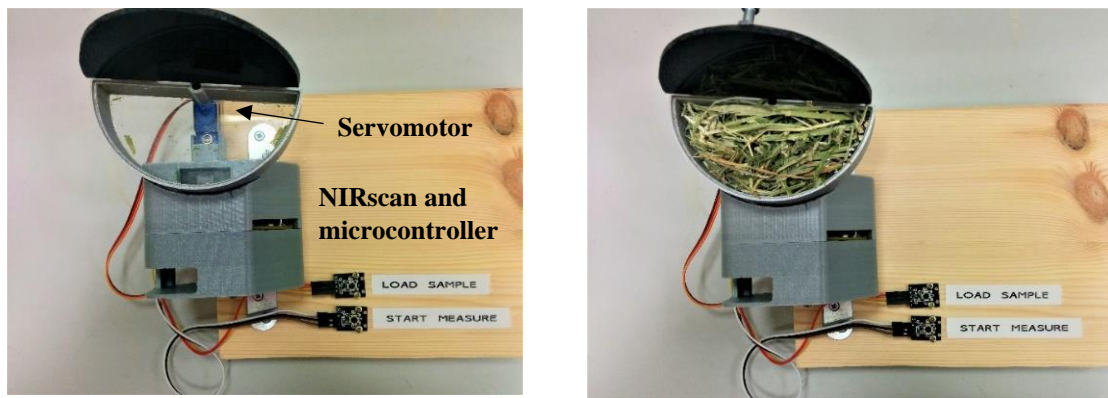
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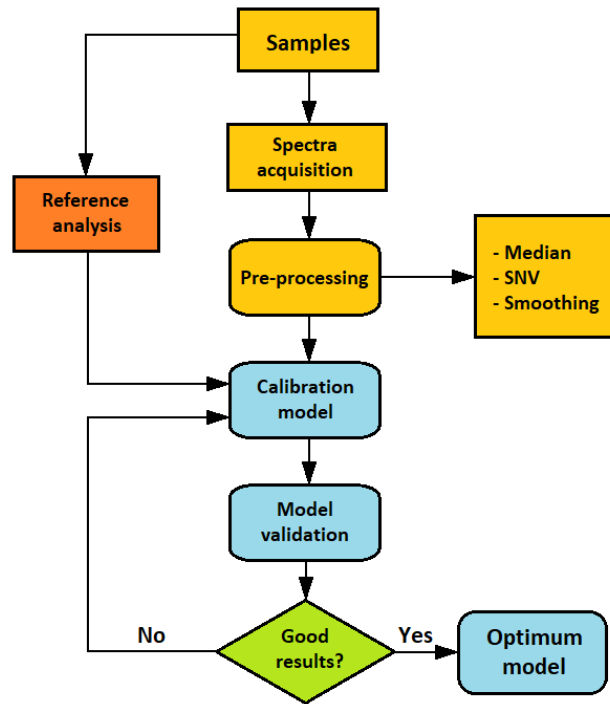
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414 **Fig. 4.** NIRS system showing the sample holder (a) without alfalfa and (b) sample holder with  
415 alfalfa.

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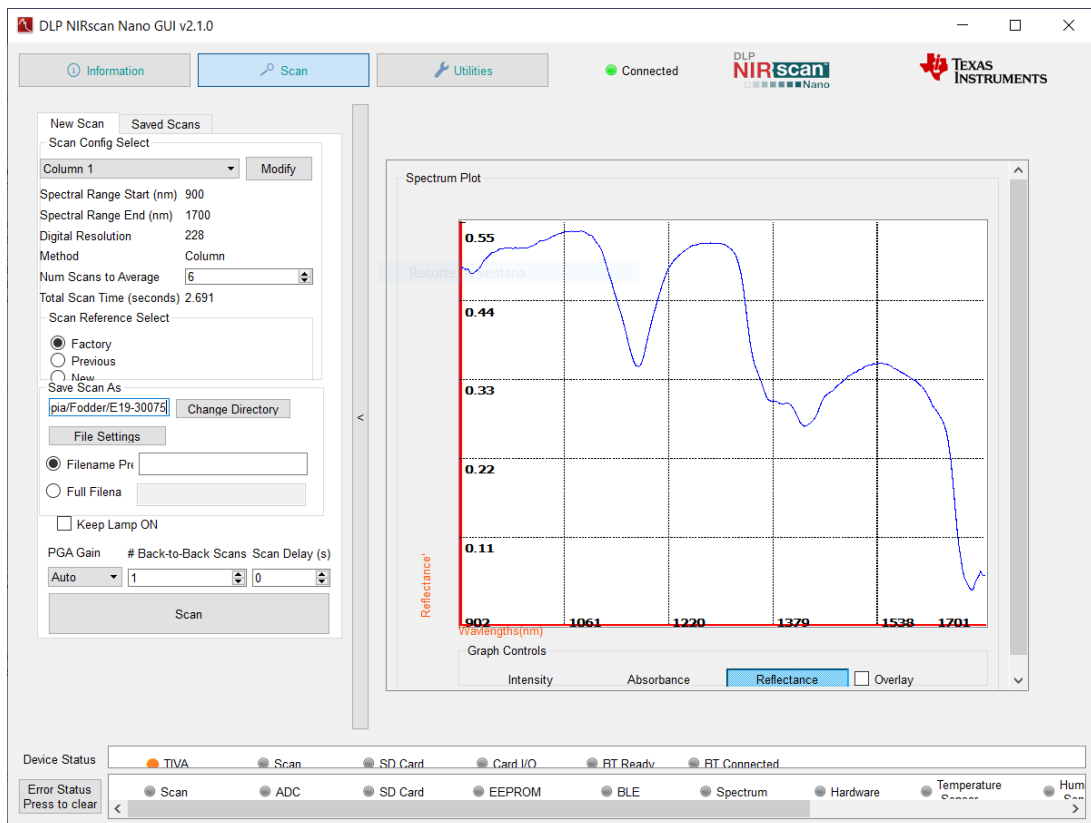
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419 **Fig. 5.** Process to obtain the chemometric model.

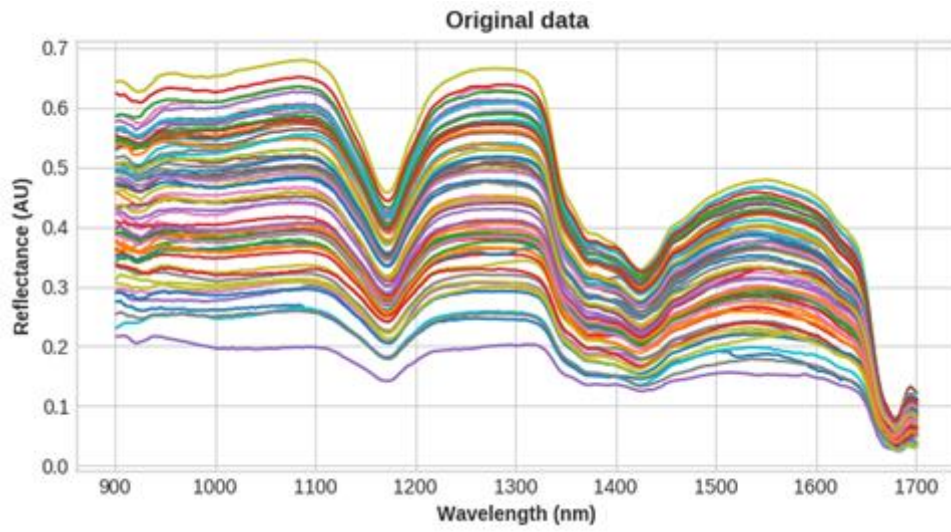
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422 **Fig. 6.** NIRscan Nano GUI scan screen.

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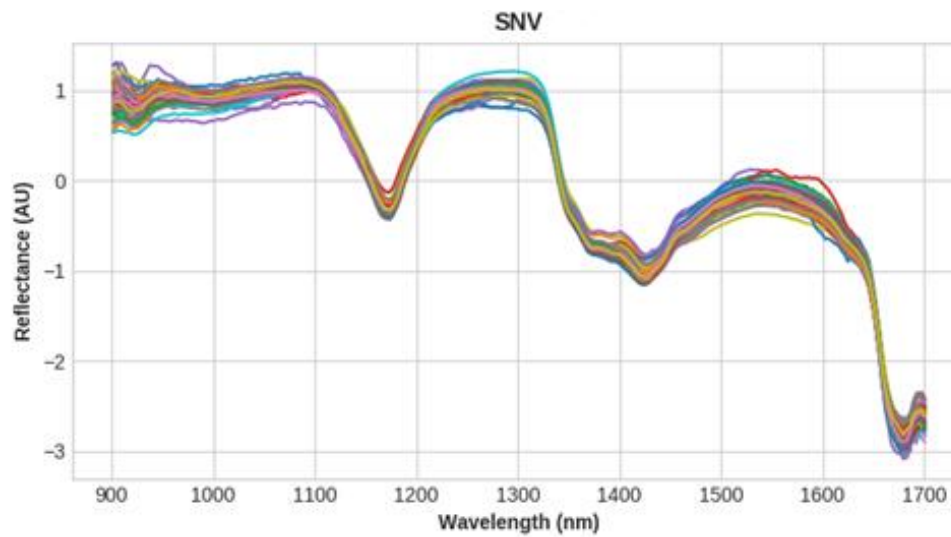


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425 **Fig. 7.** Spectra of alfalfa samples ( $N = 90$ ).

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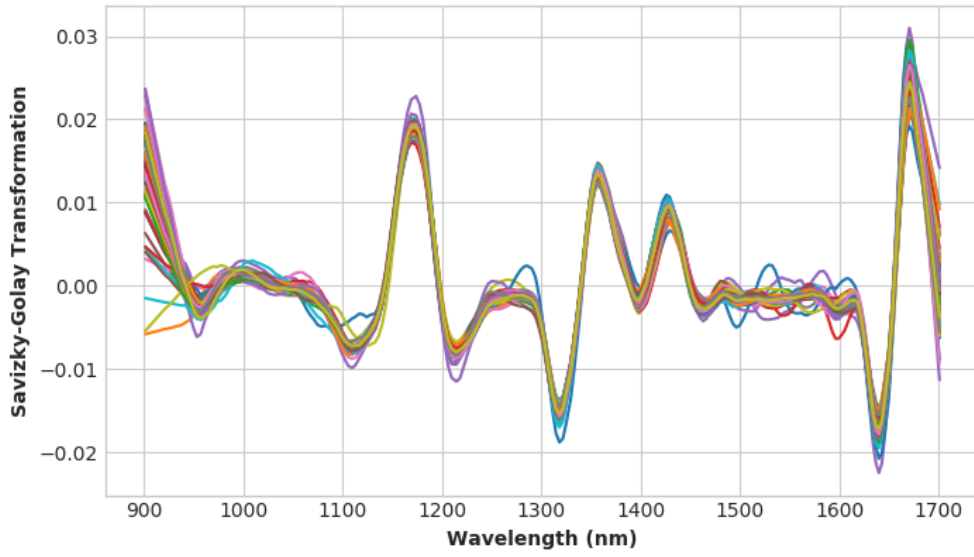


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429 **Fig.8.** Spectra after applying SNV correction to alfalfa samples.

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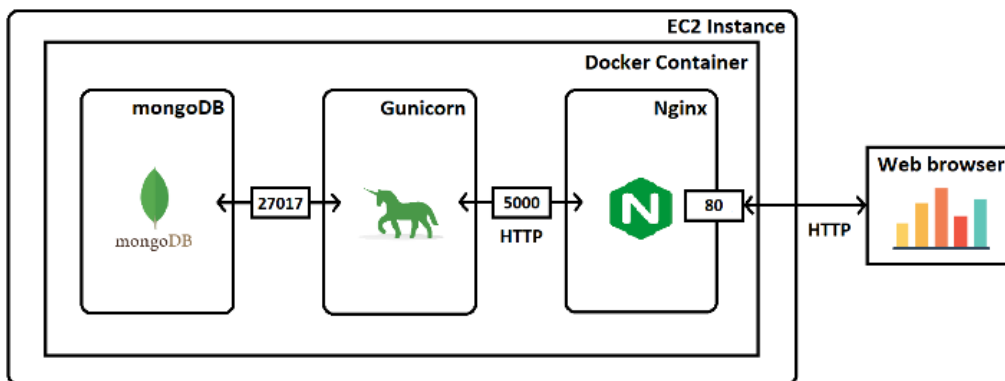


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433 **Fig. 9.** Savitzky–Golay filter applied to alfalfa sample data.

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437 **Fig. 10.** Dashboard structure on the cloud.

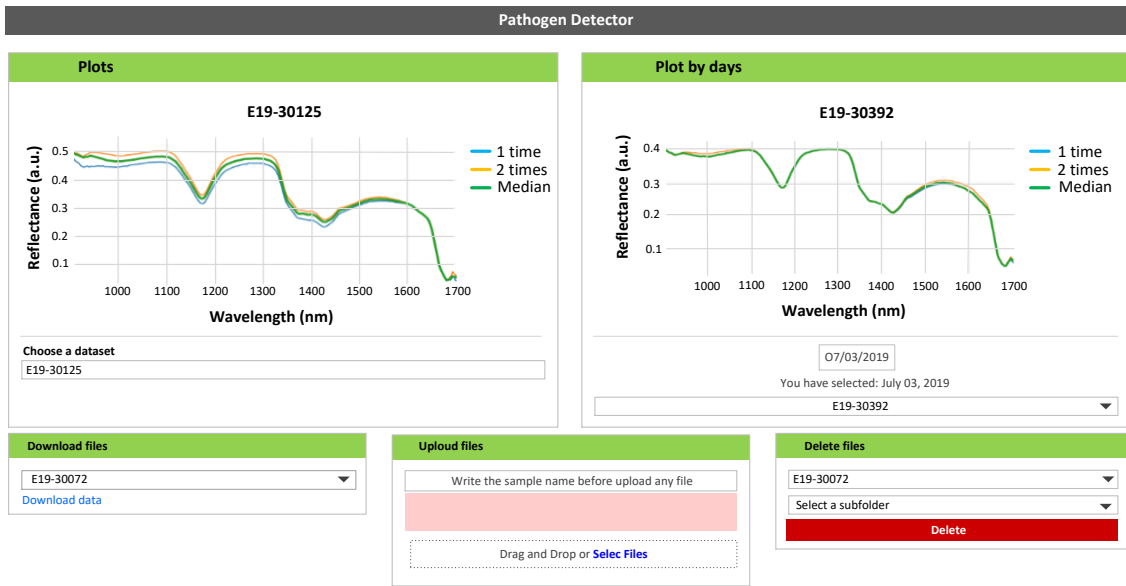
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444 **Fig. 11.** Dashboard for user visualization.

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