Quest Journals
Journal of Research in Agriculture and Animal Science
Volume 8 ~ Issue 6 (2021) pp: 07-11
ISSN(Online) : 2321-9459
www.questjournals.org

Research Paper

Prediction of Dry Matter and Crude Fiber Contents of Bagasse Using Artificial Neural Network Based on Near Infrared Absorbance Data

Sri Welia Putri[1], Adrizal[2], Rusmana Wijaya Setia Ningrat[2], Andasuryani[3]

[1]*Postgraduate Program Faculty of Animal Science, Andalas University, Padang, Indonesia*
[2]*Lecturer at the Faculty of Animal Science, Andalas University, Padang, Indonesia*
[3]*Lecturer at the Faculty of Agricultural Technology, Andalas University, Padang, Indonesia*

ABSTRACT: *Bagasse is the waste from milling sugarcane into brown sugar, which is a source of forage replacement fiber which is able to meet the needs of ruminants. The method used to determine the nutrient contents of bagasse which is often used is the conventional method which requires expensive costs, long processing time, leaves chemical waste and requires trained experts. This study aims to develop and determine the accuracy of the application of artificial neural networks (ANN) using NIR absorbance data in predicting the nutritions contents of bagasse. This study used a sample of bagasse with the amount used during calibration and validation of 43 samples for the prediction of dry matter and 37 samples for crude fiber. NIR spectrum data is obtained using a Portable Fourier Transform Near Infrared (FT-NIR) with a wavelengths range from 1000 nm - 2500 nm. NIR spectrum processing was carried out by pre-treatment the data with the standard normal variate (SNV) method using unscrambler software and the data treatment method using stepwise multiple linear regression (SMLR) with IBM SPSS Statisctic 21 software.) obtained by adding the number of input variables, the number of nodes in the ANN hidden layer (3,5,7,9), and the number of iterations (25000, 30000, 35000, 40000). The best prediction results show the standard error of prediction (SEP) and coefficient variation (CV) values respectively were 1.54% and 4.28% for dry matter content and 1.36% and 3.03% for crude fiber predictions. Based on the results, it can be concluded that ANN is able to predict dry matter and crude fiber content with an accurate model.*

KEYWORDS: *Bagasse, SMLR, NIR, ANN*

Received 25 May, 2021; Revised: 06 June, 2021; Accepted 08 June, 2021 © The author(s) 2021. Published with open access at www.questjournals.org

I. INTRODUCTION

Bagasse is a source of forage replacement fiber which is able to meet the needs of ruminants. Bagasse has a very varied nutritional content due to the number of components of the sugarcane shell in the bagasse. Besides, it is also influenced by the quality of the sugarcane that is pressed, as well as the climatic conditions where the sugarcane is planted. In preparing the ration, knowing the nutrient content of the ingredients is the first step that must be taken, however the variation in the nutrient content of bagasse causes farmers to analyze the nutrient content of each replacement of the bagasse used. This condition is very difficult for farmers, if the analytical method used is conventional methods or chemical methods such as proximate analysis.

Conventional methode to determine the nutrient content requires a long time, is expensive, leaves chemical wastes, and requires trained experts [1]. Therefore, in order to increase work efficiency and effectiveness, a method that is fast prediction, inexpensive and accurate is needed. One method that can be applied is near infrared (NIR) technology. NIR is able to predict the physical and chemical properties of a single spectrum and provide fast spectra [2], is able to analyze samples in seconds and does not require complicated sample preparation [3]. The application of NIR has been investigated in prediction the chemical composition of forage [1], then the use of NIRS is also carried out in estimating digestibility, chemical composition and digestibility of silage [4],

The NIRS method has a weakness, namely that the prediction results cannot be used directly, so to obtain the expected information from the NIR spectrum, calibration and validation are necessary. Calibration is

*Corresponding Author: sriwelia.p@gmail.com

carried out to determine the relationship between NIRS spectra data and the measured data from chemical analysis results, while validation is needed to test the accuracy of the equations of the calibration model built. The method for analyzing the spectrum that can be used is an artificial neural network (ANN).

An artificial neural network (ANN) is an analytical method that mimics the workings of biological neural networks to process the signals transmitted by the nerves to the human senses. ANN is composed of nerves organized in groups called layers, namely the input layer, hidden layer, and output layer. The advantage of the ANN method is that it can form nonlinear functions and only requires input and output data without clearly knowing the processes that occur in the ANN. Thus it is estimated that ANN is able to predict more accurately.

So far there has been no study on estimating the nutritional content of bagasse by implementing ANN using NIRS absorption data, so that later it is expected to make it easier for breeders to formulate rations according to the nutritional content of the ingredients used.

II. MATERIALS AND METHODS

Materials

The research material used was a sample of bagasse from Agam Regency and Solok Regency. The number of bagasse samples collected was 60 samples with a fresh weight of 1 kilogram per samples, but those that can be used for calibration and validation are only 43 samples for dry matter and 37 samples for crude fiber. The tools used in this research are for proximate sample chemical testing using laboratory equipment, while for non-destructive prediction of chemical content using a set of NIRS tools, namely the portable Fourier transform near infrared (FT-NIR).

Chemical analysis

Aimed at obtained the chemical content value of bagasse which will be used as a reference value in ANN training to build a prediction model. Proximate determination of the chemical content of bagasse was carried out using the standard method [6].

***Scanning* NIR**

Scanning NIR is carried out by applying the FT-NIR device to a bagasse sample with a tools based on [7]. NIR scanning results are in the form of absorbance data or (Log 1 / R) spectrum in the wavelengths range from 1000-2500 nm or in waves figures 4000–10000 cm-1.

***Pre-treatment* Data**

With the aim of improving the performance and performance of NIRs in forming prediction models, pre-treatment is carried out using the standard normal variate (SNV) method. using Unscrambler software.

***Treatment* Data**

Aims to see the correlation between NIR wavelengths and nutrient content, data treatment was carried out using the stepwise multiple linear regression (SMLR) method using IBM SPSS Statistic 21 software. The output generated from the SMLR was in the form of variable data which would later be used as ANN input.

***Training* ANN**

ANN consists of three layers, namely the input, output and hidden layers. The output of ANN training is a weighted value that is used as input in predicting nutrient content during validation. The number of nodes in the hidden layer and the number of iterations were studied to obtain the optimal weighting value in order to obtain the most accurate prediction results with low error values. ANN training performance can be measured based on the standard error of calibration (SEC) which is calculated by the formula [8]:

$$SEC = \sqrt{\frac{\Sigma(Xa-Xp)^2}{n-1}} \quad (1)$$

Information :

SEC = Standard Error Calibration (%)

Xa = Value of chemical composition by proximate analysis (%)

Xp = Estimated value (%)

n = Number of samples used in Calibration

Validation

Validation is done by prediction using weighting values obtained during ANN training based on the absorbance data selected from treatment data through SMLR with samples that were not previously used during ANN training. The validation aims to test the ability of ANN in predicting the nutrition content of bagasse. Validation success parameters can be seen from the value*standard error of prediction* (SEP), coefficient of variation (CV). The smallest SEP and CV showed the best results [9].

$$SEP = \sqrt{\frac{\Sigma(Ya-Yp)^2}{n-1}} \quad (2)$$

$$CV = \frac{SEv}{y} \times 100\% \quad (3)$$

Where :

SEP = Standard Error of Prediction (%)
Ya = Value of chemical composition by proximate analysis (%)
Yp = Value of ANN prediction results (%)
y = Average value of sample chemical composition (%)
n = The number of samples used for validation
CV = Coefficient of Diversity (%)

Place and time of research

The research was conducted at the Laboratory of Non-Ruminant Nutrition, Faculty of Animal Husbandry, Andalas University from February 2020 to August 2020.

III. RESULTS AND DISCUSSION

Variations of Nutrient Content of Bagasse

Based on the results of the proximate analysis (Table 1), the nutrient content of bagasse varies widely. Variation in the nutrient content of bagasse is caused by the number of skin components present in the bagasse. Besides, it is also influenced by the quality of the sugarcane that is pressed, as well as the climatic conditions where the sugarcane is planted. This is in accordance with the opinion [9] that the nutrient content of bagasse is influenced by climate, location, soil fertility, and the length of time the bagasse is extracted after being pressed.

Table 1. Data on the nutrient content of bagasse

Nutrient Content	Number of Samples	Minimum	Maximum	Average	Standard Deviation
Dry matter (%)	43	27.98	43.97	34.65	4.29
Crude Fiber (%)	37	38.69	50.90	44.63	3.25

In this study, the sample used as many as 60 samples produced very diverse data which caused too high an error, making it difficult to predict. In order to be uniform, elimination is carried out by removing data that are out of range (outliers). After elimination, it turned out that only 43 samples could be used for calibration and validation of the estimated dry matter content and 37 samples for crude fiber content.

Sugarcane Bagasse NIR Absorbance Spectrum

The bagasse NIR spectrum data obtained is in the form of absorbance data (Figure 1), namely the portion of the radiation beam that is absorbed when it hits the sample. In Figure 1, it can be seen that the NIR absorbance spectrum of bagasse produced has a wavelength of 1000 - 2500 nm with a vertical scale spectrum ranging from -2 to 12 with the same pattern, but in some waves it has a gap that is far enough to indicate high noise and is visible. some outliers of data, so that data pre-treatment is needed in order to minimize unwanted effects so that a more accurate and stable model is obtained. The pre-treatment of data in this study used the standard normal variate (SNV) method. Standard normal variate (SNV) is one method to reduce the deviation caused by the scattering nature of materials [10]. The absorbance spectrum data of bagasse NIR SNV can be seen in Figure 2.

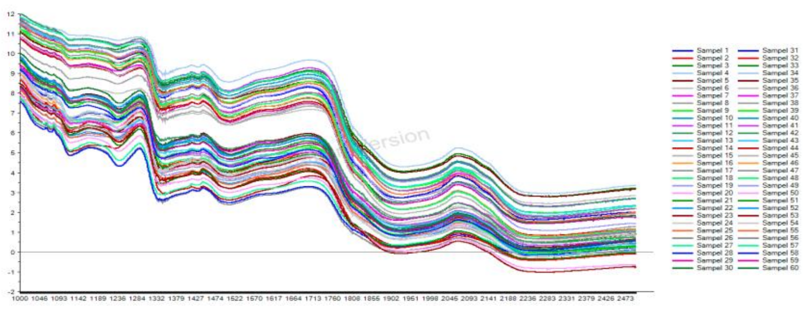

Figure 1. The NIR absorbance spectrum of bagasse

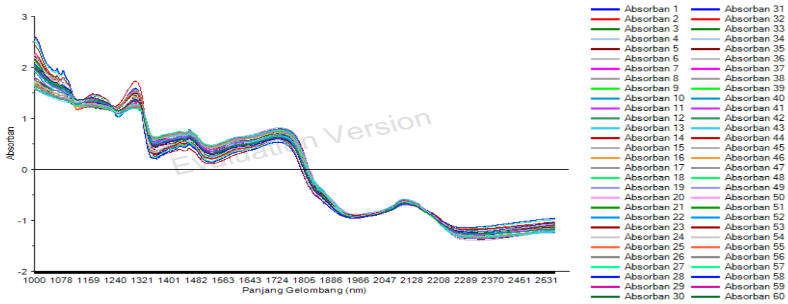

Figure 2. Absorbance spectrum for bagasse NIR-SNV

If seen in Figure 2, the resulting bagasse NIR spectra are denser than without pre-treatment so as to reduce noise, the difference in absorbance results produced after pre-treatment is influenced by the mean spectrum value and standard deviation of each sample. In the absorbance spectrum there is absorption of certain components at the peak waves of 1000 nm, 1116 nm, 1305 nm, 1443 nm, 1686 nm - 1736 nm, 2085 nm - 2107 nm, for example dry matter at a wavelength of 1420 nm - 1800, and crude fiber at a wave 1100 nm - 1300 nm [11]. However, specifically these absorption peaks cannot explain the nutrient content of the ingredients directly.

Results of the SMLR Analysis

The correlation of the nutrient content of bagasse with NIR absorbance is shown in Table 2.

Table 2: Correlation of nutrient content and NIR absorbance in bagasse as a result of SMLR analysis

No.	Nutrient content	Wavelengths	Coefficient correlation (r)
1	Dry matter	2344 nm, 2211 nm, 1159 nm, 1458 nm, 1287 nm, 2468 nm	0.90
2	Crude fiber	1808 nm, 2024 nm, 1913 nm, 1747 nm, 2036 nm, 1447 nm	0.92

In the table the selected wavelengths variable will be used as input in the ANN. The number of variables selected for dry matter and crude fiber content is 6 wavelengths with a correlation coefficient respectively were 0.90 and 0.92.

The performance of the prediction of the nutrient content of bagasse

Prediction of the nutrient content of bagasse was carried out by using ANN training using 6 input variables. Calibration is done with the number of vertices 3, 5, 7 and 9 on the hidden layer. The number of iterations used ranges from 25000 to 40000. Increasing the number of excessive iterations during training can cause overfitting where the resulting weighting value is only suitable for calibration samples marked with a low SEC value even close to zero, but not suitable for other samples. From several combinations of the number of inputs, the number of nodes in the hidden layer and the number of iterations trained on the ANN, the best prediction model is obtained which is presented in Table 3.

Table 3. Recapitulation of the SEP and CV values of the prediction of the nutrient content of bagasse

Nutrient content	Number of ANN input variables	The number of ANN hidden layer nodes	Number of iterations	SEC (%)	SEP (%)	CV (%)
Dry material	6	3	30000	1.74	1.54	4.28
Crude fiber	6	9	25000	2.94	1.36	3.03

Information :
Input = Selected variables from the absorbance data of the SMLR result
SEC = Standard Error of Calibration
SEP = Standard Error of Prediction
CV = Coefficient of Variation

Based on Table 3, it can be seen that the prediction results of the best dry matter content were obtained by ANN which has 3 nodes in the hidden layer with 30000 iterations. The prediction results gave a SEP value of 1.54% and a CV of 4.28%. Meanwhile, for crude fiber content, the best prediction model is obtained by ANN which has 9 nodes in the hidden layer with 25000 iterations during training. This is indicated by the low value of SEP (1.36%) and CV (3.03%). The accuracy of the prediction results of dry matter and crude fiber content is

*Corresponding Author: sriwelia.p@gmail.com

quite high (CV <5%). This is in accordance with the opinion[8] who stated that the ideal CV is ≤ 5%. The rules in determining the number of inputs, the number of nodes and the number of iterations in ANN training have not been found, can only be assessed from trial and error and need to be tried [12].

IV. CONCLUSION

Based on the research results, it can be concluded that the resulting ANN model is able to predict dry matter and crude fiber content accurately and can be applied.

V. RECOMMENDATION

To increase the accuracy of the prediction results of this study, further research should be carried out with a larger number of samples and to increase the speed in predicting it should be developed to develop ANN which is able to facilitate simultaneous input and output, so that the prediction of dry matter, crude fiber, crude fat and crude protein content can be predicted. done at once

REFERENCES

[1]. Parrini S, Acciaioli A, Crovetti A, Bozzi R. 2017. Use of FT-NIRS for determination of chemical components and nutritional value of natural pasture. Intal J Anim Sci. 1 (1): 1-5.

[2]. Marengo E, Bobba M, Robotti E, Lenti M. 2004. Hydroxyl and acid number prediction in polyester resins by near infrared spectroscopy and artificial neural networks. Anals Chim Acta. 511: 313-322.

[3]. Guggenbitchler W, Huck CW, Kobler A, Popp M, Bonn GK. 2006.Near infrared spectroscopy, cluster and multivariate analysis - contributions to wine analysis. J Food agric Environ. 4: 98-106.

[4]. Liu L, Han L, Yang Z, Xu Ch. 2008. Prediction of silage digestibility by near infrared reflectance spectroscopy. J Anim Feed Sci. 17: 631-639.

[5]. Andueza D, Picard F, Dozias D, Aufrere J. 2017. Fecal near-infrared reflectance spectroscopy prediction of the feed value of temperate forages for ruminants and some parameters of the chemical composition of feces: efficiency of four calibration strategies. DOI: 10.1177 / 0003702817712740.

[6]. AOAC. 1999. Official ethods of analysis. 16th ed .; AOAC International, Maryland USA.

[7]. Munawar, A. A., and Budiastra, I. W. 2009. Non-destructive Inner Quality Prediction in Intact mango with Near Infrared Reflectance Spectroscopy. Jurnal Keteknikan Pertanian IPB, 23 (1).

[8]. Mattjik, AS and I Made, S., 2006. Experimental Design with SAS and MINITAB Applications. Bogor: IPB Press.

[9]. Adrizal. 2007. Estimation of Nutrient Composition of Fish Meal with Artificial Neural Networks Based on Near Infrared Absorption. Dissertation. Graduate School, Bogor Agricultural University. Bogor.

[10]. Christiyanto, M and Agus Subrata. 2005. Physical and Biological Treatment of Agricultural Industry Waste to Crude Fiber. Activity Report. Center for Agribusiness and Agroindustry Studies, Diponegoro University. Semarang.

[11]. Rinnan A, Van den Berg F, Engelsen SB. 2009. Review of the most common pre-processing techniques for near-infrared spectra. Trends Anal Chem 28: 1201-1222.

[12]. Osborne BG, Fearn T, Hindle PH. 1993. Pratical NIR Spectroscopy with Applications in Food and Beverage Analysis. Singapore: Longman Publishers.

[13]. Ali, TH; Mohd, HB S; and Ahmed NA 2018. "Prediction of Small Hydropower Plant Power Production in Himreen Lake DAM (HLD) using Artificial Neural Network," Alexandria engineering journal. Vol. 57, pp. 211–22