*Quest Journals*
*Journal of Research in Agriculture and Animal Science*
*Volume 8 ~ Issue 5 (2021) pp: 48-55*
*ISSN(Online) : 2321-9459*
www.questjournals.org

**Research Paper**

# Prediction of Dry Matter, Crude Protein and Crude Fiber of Cabbage Waste Using Artificial Neural Networks Based on Nirs Absorbance Data

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***ABSTRACT:*** *The purpose of this study was to evaluate the accuracy of the value obtained from the comparison of proximate analysis with the results of the analysis using artificial neural networks. This study used 53 samples of cabbage waste. Cabbage waste is obtained in the areas of Solok Regency and Agam Regency, West Sumatra, Indonesia. The pretreatment used is Normalize with the principal component analysis (PCA) method. The parameters analyzed were dry matter, crude protein and crude fiber. The results showed that the artificial neural network with a model that had been built could not predict crude fiber well. This is indicated by the value of standard error of prediction (SEP), coefficient of variation (CV), and the ratio between standard deviation and standard error of prediction (SD / SEP) which is high (crude fiber = SEP: 0.92%, CV: 6, 61% and SD / SEP: 1.02%). Artificial neural network can predict dry matter and crude protein content of cabbage waste well (dry matter = SEP: 0.70%, CV: 4.77%, SD / SEP: 2.07%, crude protein = SEP: 1.30%, CV: 8.05% and SD / SEP: 2.58%,).*

***KEYWORD:*** *Artificial Neural Network, Near Infrared Spectroscopy, Proximate Analysis, Principal Component Analysis, Cabbage Waste.*

*Received 14 May, 2021; Revised: 28 May, 2021; Accepted 30 May, 2021* 

## I. INTRODUCTION

Cabbage is a vegetable crop that produces a lot of waste. Cabbage waste can be found on agricultural land after the harvest period. The high production of cabbage has resulted in waste that has not been used optimally for animal feed. Cabbage production in Solok Regency was recorded at 47765.30 tons and in Agam Regency it was recorded at 15233.70 tons [4]. In its use, breeders must know the nutritional content of cabbage waste that will be used as animal feed. The method that can help breeders is the proximate analysis method.

The proximate analysis method to determine the chemical composition of foodstuffs takes a long time and is expensive [1]. Over the years a number of instrumentation techniques have been developed to determine the chemical composition of a feed ingredient quickly and easily. The technique in question is a near infrared spectroscopy measurement technique which can be emitted by infrared light from the material / sample. Near infrared spectroscopy has been proven to be able to measure a variety of quality features well [5] [9].

Techniques that can support the use of NIRS to predict the chemical composition of cabbage waste are modeling techniques based on artificial intelligence systems or artificial neural networks. Research using near infrared spectroscopy has been widely studied by previous researchers. Based on [2] conducting an analysis of the estimation of the nutrient composition of fish meal with artificial neural networks based on near infrared absorption, the treatment methods used in this study are stepwise multiple linear regression (SMLR) and principal component analysis (PCA). Based on [7] conducted an analysis of the freshness evaluation of cabbage using near infrared spectroscopy.

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## II. MATERIALS AND METHODS

**Research material**

The materials used in this study were 53 samples of cabbage waste obtained from Solok and Agam districts, West Sumatra, Indonesia.

**Research Methods**

**Sample Preparation**

The sample used in this study is a fresh weight of 1 kilogram / sample obtained from various farmers in two different locations.

**Scanning Near Infrared Spectroscopy**

Near infrared spectroscopy (NIRS) data of all cabbage waste flour samples were obtained and collected using a portable Fourier transform near infrared (FT-NIR) According to [6] Configured workflows are developed to control and operate instruments based on settings.

**Proximat Analysis**

**Dry mater (%)**

Dry the porcelain dishes in an oven at 110oC for 1 hour. Then chill in a desiccator for 15 minutes. Then weighed (A). The sample is put into a porcelain dish about 1 gram (B). then put the porcelain plate containing the sample into the oven at 110 C for 8 hours, cooled into a desiccator for 15 minutes, then the porcelain plate containing the sample was weighed (C).

Water content formula:

$$\text{Water concentration (\%)} = \frac{A+B-C}{B} \text{x } 100\%$$

$$\text{Dry matter (\%)} = 100\ \% - \text{water consentration \%}$$

Information : A = weight of the porcelain cup (gram)

B = sample weight (gram)

C = weight of the porcelain dish containig the sample after oven (garam)

**Crude Protein (%)**

**Digestion**

Enter 1 gram of sample into the Kjeldahl flask (X), add 1 gram of selenium and 10 ml of concentrated H2SO4. After that, digest it in a fume hood until the solution is clear, then let it cool.

**Distillation**

After digestion, the sample is diluted with distilled water into a 250 ml volumetric flask. Then prepare a distilled flask for distillation to which 150 ml of distilled water, 25 ml of NaOH, and 25 ml of the diluted sample have been added. Then make the MM indicator, enter 25 ml H2SO4 into Erlenmeyer, add 5 drops of the MM indicator. Close the flask and heat it, then connect the MM indicator to the end of the distillation tool, wait 40 minutes. Just take the sample and clean the tool with distilled water.

**Titration**

The MM indicator resulting from the distillation is titrated using 0.1 N NaOH until the color changes from pink to yellowish, which indicates the end of the titration process (Z). Then make a blank (Y).

Crude protein formula:

$$\text{Crude protein (\%)} = \frac{(Y-Z)\text{x N x } 0{,}014 \text{ x C x } 6{,}25}{\mathbf{X}} \text{x}100\%$$

**Crude Fiber (%)**

Filter paper oven for 1 hour at a temperature of 110 $^{o}$C cool in a desiccator for 15 minutes, then weigh (A). The sample was weighed 1 gram (B) and put it in the beaker. Then heat it with 100 ml of $H_2SO_4$ for 40 minutes. Rinse with 100 ml hot water 2 times rinse. Fold and put in the beaker, reheat it with 0.3 100 ml of NaOH for 40 minutes. Rinse with 3x hot water, rinse 150 ml. Then the last rinse with 25 ml acetone. After drying, fold it and put it in a porcelain dish and dry it in an oven at 110 $^{o}$C for 6 hours. Cool in a desiccator for 20 minutes, then weigh (C). Then heated in the furnace for 4 hours. Put in 110 $^{o}$C oven for 1 hour, cool in a desiccator for 20 minutes then weigh (D).

Crude fiber formula:

Information: A = weight of filter paper (grams)

B = sample weight (grams)

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C = weight before sowing (grams)
D = weight after being planted (grams)

**Calibration**

Calibration is done through the Tranning Artificial Neural Network. The number of samples used for calibration was 33 samples. The calibration activities carried out were NIRS scanning, data pretreatment, data treatment and artificial neural network training.

a**. Pretreatment**

This study used a normalize pretreatment with unscramble software. Initial data generated before pretreatment may result in outliers. Therefore, the presence of pretreatment can help refine the initial data.

b**. Treatment Data**

The purpose of data treatment is to prepare input that will be processed by the artificial neural network. Data treatment includes reduction of input data variables and data normalization. Reducing the number of variable data can avoid overvitting and normalization can align input and output data according to the existing data range. In this study, a principal component analysis (PCA) method was used with the IBM Statistics 21 software.

**c. Artificial Neural Network**

The results obtained from the treatment data can be used as input to the artificial neural network. The artificial neural network training aims to determine the weighted value that is used as an input value to predict the validation period.

d. **Data Analysis**

The calibration results can be measured by standard error of calibration (SEC) with the formula:

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

Information: SEC = standard error of calibration (%)
Xa = referent value (%)
Xp = estimation result (%)
n = number of calibration samples

**Validation**

The number of samples used for validation was 20 samples of cabbage waste. Validation results can be obtained by inputting the results obtained from the calibration and weighting values. So that the output that will be obtained is the result of validation. To find out the success parameters, it can be seen from the standard error of prediction (SEP) and the coeffisient of variation (CV).The number of samples used for validation was 20 samples of cabbage waste. Validation results can be obtained by inputting the results obtained from the calibration and weighting values. So that the output that will be obtained is the result of validation. To find out the success parameters, it can be seen from the standard error of prediction (SEP) and the coeffisient of variation (CV).

$$\text{SEP} = \sqrt{\frac{\sum(Ya-Yp)^2}{n-1}} \qquad \text{CV} = \frac{\text{SEP}}{y} \text{ x } 100\ \%$$

Note: SEP = standard error of prediction (%)
Ya = referent value (%)
Yp = estimation result (%)
n = number of validation samples
CV = coeffisient of variation (%)
y = average referent value (%)

**Place and Time of Research**

This research was conducted in the non-ruminant nutrition laboratory, Faculty of Animal Science, Andalas University, Padang, Indonesia.

## III. RESULT AND DISCUSSTION

**Chemical Composition of Cabbage Waste**

Cabbage waste was analyzed using 2 methods, namely chemical methods and near infrared spectroscopy methods. The results of chemical analysis data can be seen in table 1. The average value of the dry matter of

cabbage waste is 14.12%. Crude protein 17.85%, crude fiber 14.31%. Based on [3] states that the nutritional value of cabbage leaves is 9.90% dry mater, 21.50% crude protein, 12.90% crude fiber. The difference in the value of the chemical composition of cabbage waste with supporting data is due to differences in where to obtain samples, places to analyze samples and different research times. Standard deviation (SD) describes the degree of diversity of data within a population. The results of chemical analysis explained that the smallest standard deviation was found in crude fiber with SD 1.96%, and the highest was in crude protein with SD 4.95%. This shows that the standard deviation of crude fiber has almost uniform values, while for dry material and crude protein, the data is more varied.

Table 1. Chemical composition of dry mater, crude protein and crude fiber cabbage waste

| Composition | Minimum (%) | Maksimum (%) | Average (%) | Standard deviation (%) |
|---|---|---|---|---|
| Dry mater | 11.56 | 16.68 | 14.12 | 2.56 |
| Crude protein | 12.90 | 22.80 | 17.85 | 4.95 |
| Crude fiber | 12.34 | 16.27 | 14.31 | 1.96 |

**Absorbance Data Near Infrared Spectroscopy of Cabbage Waste**

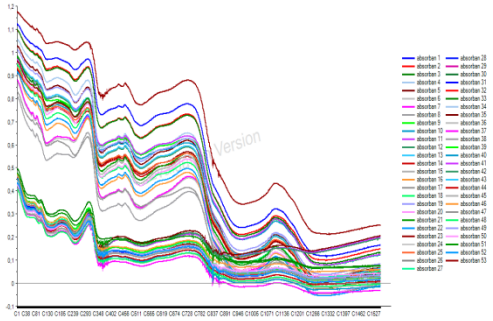

Figure 1. the absorbance of raw cabbage waste

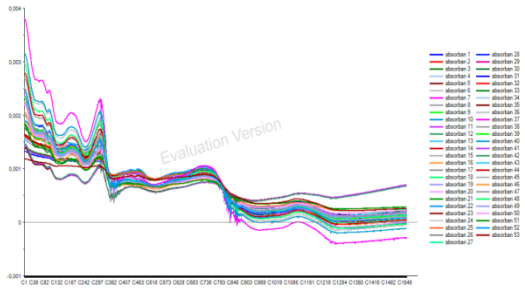

figure 2. Pretreatment absorbance data

Absorption acquisition is carried out at a wavelength range of 1000-2500 nm with intervals ranging from -0.1 to 1.2. The acquisition was carried out on 53 samples of cabbage waste. The initial absorption of cabbage waste can be seen in Figure 1.

Wavelengths of 1000-2500 nm can be seen at the absorption forming several peaks. Each peak describes the chemical composition contained in cabbage waste. In addition, the absorption shows that they do not overlap, so it can be concluded that each sample of cabbage waste has a varying chemical composition.

Absorption pretreatment was carried out to remove the absorption noise. The method used is the normalize method using the unscramble application. The absorbance data after pretreatment can be seen in Figure 2.

Figure 1 and Figure 2 explain the difference between pretreatment and non-pretreatment absorption. The normalize method is used to scale the sample to achieve certain properties. This is done to reduce the influence of noise wave interference, so that the absorption becomes smoother.

**The Results of The Prediction of Nutritional Content Using Artificial Neural Networks**

**Dry matter**

The results of the calibration and validation of the dry matter content of cabbage waste using the ANN model can be seen in Table 2 and Table 3.In the dry matter content of the waste cabbage calibration with normalize pretreatment treatment with the number of PC 6 40000 iterations on hidden layer 7 which results in a SEC value = 0.26% and CV = 1.94%. And the dry matter content of cabbage waste was validated by pretreatment normalize with the number of PC 4, 30000 iterations on hidden layer 9 resulted in the value of SEP = 0.70%, CV = 4.77%, SD / SEP = 2.07%.

The results of the cabbage waste calibration using the artificial neural network method showed a better value than using the partial least square (PLS) method with pretreatment normalize which was carried out [8] regarding the chemical content of Gayo Arabica coffee beans with a value of r = 0.90%; SEC = 0.28%; SEP = 0.30%; CV = 2.16% and the ratio of standard deviation to standard error (RDP) = 3.15. The results of the validation model using the neural network method have a lower CV value than the partial least square method. The results of the validation model have a value of SD / SEP> 2 indicating a model has a fairly good accuracy

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value. This proves that the ANN method can improve the accuracy of the model used to predict the value of cabbage waste content.

Overall, the variation in the number of PCs is not much different. But in choosing the best treatment in a calibration model development, the consistency value or comparison between SEC and SEP is a condition of acceptance of the calibration model. According to [10] the SEC value that differs slightly from the SEP indicates high precision, so that the data bias is low. The greater the RDP value also shows that the model has good accuracy, and the correlation coefficient (CV) value is closer to 1 (r = 1). So that the consistency value is seen whether it meets the requirements or not. According to [8] that the RDP value between 1.5-1.9 shows that the prediction is still rough and still needs improvement in the calibration. Meanwhile, the RDP value between 2-2.5 shows a fairly good prediction model. While the RDP value is between 2.5-3 or more, which indicates a good and very good accuracy of the prediction model.

Table 2. the effect of the number of PC, the number of iterations and the number of nodes in the hidden layer of the artificial neural network on SEC (%) dry matter calibration

| Number of PC | Number of Iteration (000) | The Number of nodes on hidden layer artificial neural network | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 3 | | 5 | | 7 | | 9 | |
| | | SEC | CV | SEC | CV | SEC | CV | SEC | CV |
| | | % | | | | | | | |
| 2 | 25 | 1.71 | 12.22 | 1.94 | 13.97 | 1.6 | 11.04 | 1.19 | 8.60 |
| | 30 | 1.41 | 9.85 | 1.82 | 13.13 | 1.29 | 9.34 | 1.27 | 9.31 |
| | 35 | 1.70 | 12.49 | 1.47 | 10.3 | 1.17 | 8.32 | 1.05 | 7.82 |
| | 40 | 1.81 | 13.19 | 1.57 | 11.3 | 0.94 | 6.97 | 1.86 | 13.59 |
| 4 | 25 | 0.80 | 5.69 | 0.75 | 5.40 | 0.68 | 4.70 | 0.68 | 4.93 |
| | 30 | 0.70 | 4.86 | 0.34 | 2.46 | 0.65 | 4.70 | 0.66 | 4.85 |
| | 35 | 0.46 | 3.37 | 0.60 | 4.34 | 0.42 | 3.00 | 0.53 | 3.98 |
| | 40 | 0.85 | 6.20 | 0.65 | 4.72 | 0.42 | 3.15 | 0.63 | 4.61 |
| 6 | 25 | 0.74 | 5.40 | 0.47 | 3.43 | 0.76 | 5.26 | 0.69 | 5.00 |
| | 30 | 0.70 | 4.90 | 0.43 | 3.17 | 0.61 | 4.40 | 0.60 | 4.41 |
| | 35 | 0.48 | 3.49 | 0.57 | 4.17 | 0.44 | 3.09 | 0.39 | 2.89 |
| | 40 | 0.33 | 2.38 | 0.44 | 3.23 | 0.26 | 1.94 | 0.63 | 4.59 |

Table 3. the effect of the number of PC, the number of iterations and the number of nodes in the hidden layer of the artificial neural network on SEP (%) dry matter validation

| Number of PC | Number of Iteration (000) | The Number of nodes on hidden layer artificial neural network | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 3 | | 5 | | 7 | | 9 | |
| | | SEP | CV | SEP | CV | SEP | CV | SEP | CV |
| | | % | | | | | | | |
| 2 | 25 | 1.10 | 7.78 | 1.31 | 9.12 | 1.45 | 10.57 | 1.85 | 12.70 |
| | 30 | 1.58 | 11.51 | 1.32 | 9.35 | 0.95 | 6.43 | 1.28 | 8.72 |
| | 35 | 1.51 | 10.20 | 1.14 | 8.16 | 1.17 | 8.49 | 1.46 | 9.39 |
| | 40 | 1.18 | 8.10 | 1.06 | 7.20 | 1.45 | 9.79 | 0.91 | 6.34 |
| 4 | 25 | 0.94 | 6.64 | 0.79 | 5.52 | 1.33 | 9.65 | 1.45 | 9.98 |
| | 30 | 0.95 | 6.94 | 1.37 | 9.74 | 1.22 | 8.29 | 0.70 | 4.77 |
| | 35 | 1.19 | 8.08 | 1.38 | 9.09 | 1.96 | 14.05 | 1.36 | 8.75 |
| | 40 | 1.26 | 8.60 | 1.70 | 11.51 | 0.97 | 6.54 | 0.84 | 5.89 |
| 6 | 25 | 0.80 | 5.46 | 1.37 | 9.37 | 1.61 | 11.73 | 0.82 | 5.64 |
| | 30 | 0.90 | 6.33 | 1.25 | 8.47 | 0.77 | 5.18 | 0.78 | 5.33 |
| | 35 | 1.08 | 7.28 | 1.27 | 8.40 | 1.39 | 10.31 | 1.28 | 8.20 |

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| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 40 | 1.84 | 12.51 | 1.55 | 10.20 | 1.55 | 10.54 | 0.98 | 6.82 |

**Crude Protein**

The results of calibration and validation of the protein content of cabbage waste can be seen in Table 4 and Table 5.In the protein content of cabbage waste, calibration using pretreatment normalize with the number of PC 6, 40000 iterations, the hidden layer 9 results in SEC values = 0.32% and CV = 199 %. The results of the cabbage waste validation model using pretreatment normalize with the number of PC 4, 35000 iterations on hidden layer 3 with the resulting SEP = 1.30%, CV = 8.05%, and SD / SEP = 2.58%. The results of the validation of the protein content of cabbage waste show that the SD / SEP value> 3 indicates the validity value of a model that has good accuracy. According to [8] the RDP value between 2.5-3 shows a good and very good predictive model. This is because protein has the highest chemical content in cabbage among other chemical contents (Table 1). The results of the validation of the protein content of cabbage waste had a low CV value. According to [10] the value of the correlation coefficient (CV) is close to 1 (r = 1). So that the consistency value is seen whether it meets the requirements or not.

Tabel 4. the effect of the number of PC, the number of iterations and the number of nodes in the hidden layer of the artificial neural network on SEC (%) crude protein calibration

| Number of PC | Number of Iteration (000) | The Number of nodes on hidden layer artificial neural network | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 3 | | 5 | | 7 | | 9 | |
| | | SEC | CV | SEC | CV | SEC | CV | SEC | CV |
| | | % | | | | | | | |
| 2 | 25 | 1.10 | 7.78 | 1.31 | 9.12 | 1.45 | 10.57 | 1.85 | 12.70 |
| | 30 | 1.58 | 11.51 | 1.32 | 9.35 | 0.95 | 6.43 | 1.28 | 8.72 |
| | 35 | 1.51 | 10.20 | 1.14 | 8.16 | 1.17 | 8.49 | 1.46 | 9.39 |
| | 40 | 1.18 | 8.10 | 1.06 | 7.20 | 1.45 | 9.79 | 0.91 | 6.34 |
| 4 | 25 | 0.94 | 6.64 | 0.79 | 5.52 | 1.33 | 9.65 | 1.45 | 9.98 |
| | 30 | 0.95 | 6.94 | 1.37 | 9.74 | 1.22 | 8.29 | 0.70 | 4.77 |
| | 35 | 1.19 | 8.08 | 1.38 | 9.09 | 1.96 | 14.05 | 1.36 | 8.75 |
| | 40 | 1.26 | 8.60 | 1.70 | 11.51 | 0.97 | 6.54 | 0.84 | 5.89 |
| 6 | 25 | 0.80 | 5.46 | 1.37 | 9.37 | 1.61 | 11.73 | 0.82 | 5.64 |
| | 30 | 0.90 | 6.33 | 1.25 | 8.47 | 0.77 | 5.18 | 0.78 | 5.33 |
| | 35 | 1.08 | 7.28 | 1.27 | 8.40 | 1.39 | 10.31 | 1.28 | 8.20 |
| | 40 | 1.84 | 12.51 | 1.55 | 10.20 | 1.55 | 10.54 | 0.98 | 6.82 |

Tabel 5. the effect of the number of PC, the number of iterations and the number of nodes in the hidden layer of the artificial neural network on SEP (%) crude protein validation

| Number of PC | Number of Iteration (000) | The Number of nodes on hidden layer artificial neural network | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 3 | | 5 | | 7 | | 9 | |
| | | SEP | CV | SEP | CV | SEP | CV | SEP | CV |
| | | % | | | | | | | |
| 2 | 25 | 1.10 | 7.78 | 1.31 | 9.12 | 1.45 | 10.57 | 1.85 | 12.70 |
| | 30 | 1.58 | 11.51 | 1.32 | 9.35 | 0.95 | 6.43 | 1.28 | 8.72 |
| | 35 | 1.51 | 10.20 | 1.14 | 8.16 | 1.17 | 8.49 | 1.46 | 9.39 |
| | 40 | 1.18 | 8.10 | 1.06 | 7.20 | 1.45 | 9.79 | 0.91 | 6.34 |
| 4 | 25 | 0.94 | 6.64 | 0.79 | 5.52 | 1.33 | 9.65 | 1.45 | 9.98 |
| | 30 | 0.95 | 6.94 | 1.37 | 9.74 | 1.22 | 8.29 | 0.70 | 4.77 |
| | 35 | 1.19 | 8.08 | 1.38 | 9.09 | 1.96 | 14.05 | 1.36 | 8.75 |

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| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 40 | 1.26 | 8.60 | 1.70 | 11.51 | 0.97 | 6.54 | 0.84 | 5.89 |
| 6 | 25 | 0.80 | 5.46 | 1.37 | 9.37 | 1.61 | 11.73 | 0.82 | 5.64 |
| | 30 | 0.90 | 6.33 | 1.25 | 8.47 | 0.77 | 5.18 | 0.78 | 5.33 |
| | 35 | 1.08 | 7.28 | 1.27 | 8.40 | 1.39 | 10.31 | 1.28 | 8.20 |
| | 40 | 1.84 | 12.51 | 1.55 | 10.20 | 1.55 | 10.54 | 0.98 | 6.82 |

**Crude Fiber**

Tabel 6. the effect of the number of PC, the number of iterations and the number of nodes in the hidden layer of the artificial neural network on SEC (%) crude fiber calibration

| Number of PC | Number of Iteration (000) | The Number of nodes on hidden layer artificial neural network | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 3 | | 5 | | 7 | | 9 | |
| | | SEC | CV | SEC | CV | SEC | CV | SEC | CV |
| | | % | | | | | | | |
| 2 | 25 | 1.23 | 8.61 | 1.48 | 10.44 | 1.20 | 8.09 | 1.07 | 7.69 |
| | 30 | 1.71 | 11.89 | 0.98 | 6.71 | 1.23 | 8.67 | 1.04 | 7.33 |
| | 35 | 1.26 | 9.06 | 1.58 | 10.95 | 1.79 | 12.71 | 1.20 | 8.49 |
| | 40 | 1.18 | 8.13 | 0.74 | 5.18 | 1.35 | 9.60 | 1.08 | 7.83 |
| 4 | 25 | 0.80 | 5.60 | 0.74 | 5.25 | 0.83 | 5.65 | 0.87 | 6.00 |
| | 30 | 0.91 | 6.32 | 0.63 | 4.30 | 0.88 | 6.21 | 0.64 | 4.50 |
| | 35 | 0.92 | 6.66 | 0.54 | 3.76 | 0.92 | 6.50 | 0.71 | 5.02 |
| | 40 | 0.87 | 5.99 | 0.65 | 4.52 | 0.78 | 5.56 | 0.86 | 6.21 |
| 6 | 25 | 0.76 | 5.31 | 0.54 | 3.82 | 0.56 | 3.76 | 0.67 | 4.82 |
| | 30 | 0.79 | 5.52 | 0.50 | 3.40 | 0.52 | 3.66 | 0.37 | 2.64 |
| | 35 | 0.71 | 5.11 | 0.52 | 3.59 | 0.44 | 3.09 | 0.54 | 3.80 |
| | 40 | 0.47 | 3.21 | 0.55 | 3.83 | 0.44 | 3.07 | 0.69 | 4.98 |

The results of calibration and validation of cabbage waste crude fiber content can be seen in Table 6 and Table 7.In the crude fiber content of cabbage waste, calibration with pretreatment normalize with the number of PC 6, 30000 iterations, the hidden layer 9 yields SEC value = 0.37%, CV = 2.64%. The results of the validation model with pretreatment normalize with the number of PC 2, 30000 iterations, the hidden layer 3 resulted in the value of SEP = 0.92%, CV = 6.61%, SD / SEP = 1.02%. The results of the validation of the crude fiber content of cabbage waste showed the SD / SEP value, 1.5 indicating a wrong prediction and the prediction model could not be used for further predictions. In addition, the results of the validation model with the artificial neural network method have a low CV value. According to [10] the value of the correlation coefficient (CV) is close to 1 (r = 1). So that the consistency value is seen whether it meets the requirements or not.

Tabel 7. the effect of the number of PC, the number of iterations and the number of nodes in the hidden layer of the artificial neural network on SEP (%) crude fiber validation

| Number of PC | Number of Iteration (000) | The Number of nodes on hidden layer artificial neural network | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 3 | | 5 | | 7 | | 9 | |
| | | SEP | CV | SEP | CV | SEP | CV | SEP | CV |
| | | % | | | | | | | |
| 2 | 25 | 1.86 | 13.20 | 1.42 | 9.85 | 2.26 | 17.47 | 2.46 | 16.64 |
| | 30 | 0.92 | 6.61 | 1.39 | 10.18 | 1.43 | 10.31 | 1.23 | 8.55 |
| | 35 | 1.81 | 12.33 | 1.35 | 9.70 | 1.00 | 7.10 | 1.38 | 9.92 |
| | 40 | 1.41 | 10.28 | 1.48 | 10.42 | 1.09 | 7.63 | 1.72 | 11.75 |
| 4 | 25 | 2.14 | 15.28 | 2.08 | 14.45 | 1.94 | 15.02 | 1.45 | 10.52 |

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| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 30 | 1.43 | 10.24 | 2.15 | 15.79 | 1.35 | 9.59 | 1.51 | 10.51 |
| | 35 | 2.35 | 15.97 | 1.78 | 12.77 | 1.47 | 10.47 | 1.37 | 9.79 |
| | 40 | 1.42 | 10.32 | 1.54 | 10.84 | 2.12 | 14.86 | 1.46 | 10.15 |
| 6 | 25 | 1.82 | 12.92 | 1.41 | 9.84 | 1.96 | 15.16 | 2.56 | 17.29 |
| | 30 | 1.15 | 8.23 | 1.40 | 10.28 | 1.20 | 8.55 | 1.73 | 12.01 |
| | 35 | 1.74 | 11.86 | 1.95 | 13.94 | 1.65 | 11.79 | 1.64 | 11.78 |
| | 40 | 1.43 | 10.40 | 1.66 | 12.00 | 1.56 | 11.13 | 1.82 | 12.45 |

## IV. CONCLUSION

The results of the study concluded that the prediction of dry matter and crude protein showed the SD / SEP value which had a fairly good and good accuracy. However, SD / SEP Crude fiber shows a value <1.5 so it cannot be used for further predictions. In addition, the correlation coefficient (CV) of dry matter, crude protein, crude fiber cannot be said to be good because the resulting correlation coefficient is > 1. So it still cannot be said to meet all the requirements of the prediction model. Validation produces standard error of prediction (SEP), coefficient of variation (CV) and ratio between standard deviation and standard error of prediction (SD / SEP), namely dry matter SEP = 0.70%, CV = 4.77%, SD / SEP = 2.07% , crude protein SEP = 1.30%, CV = 8.05% SD / SEP = 2.58%, crude fiber 0.92% and 6.61%, SD / SEP = 1.02%.

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