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Texture Feature On Determining Quantity of Soil Organic Matter For Patchouli Plant Using Backpropagation Neural Network

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Abstract. Patchouli (Pogostemon Cablin Bent) has higher PA (Patchouli Alcohol) and oil production if grown in soil containing 75% organic matter. One way that can be used to detect the content of organic matter is to use soil images. The problem in the use of soil images is the color of the soil that is almost similar, namely the gradation between dark brown to black. Therefore, color features are not enough to be used as input in the recognition process. For this purposes, texture features are added in this study in addition to color features. The color features are extracted using color moment and the texture features are extracted using Gray Level Co-occurrence Matrix (GLCM). These feature was then chosen to get the best combination as input in the identification process using the Backpropagation Neural Network (BPNN). The system identifies the quantity of soil organic matter into five classes, namely very low, low, medium, high, and very high. The highest accuracy result obtained was 73% and MSE value 0.5122 by using five GLCM features (Angular Second Moment, contrast, correlation, Inverse Difference Moment, and entropy). This result was obtained by using the BPNN parameter, namely learning rate values 0.5, maximum iteration values of 1000, number training data 210, and total test data 12.

Keyword: organic matter, soil images, texture features, backpropagation neural network

1 Introduction

Patchouli is one of the essential plants that are widely used in the cosmetic or perfume industry. Indonesia is the largest supplier of patchouli oil in the international market in 2012, which is about 85% [1]. However, the number of exports continues to decline due to the declining production of Patchouli. This export prospect should be accompanied by the development of the quality and quantity of patchouli cultivation. One way that can be done to increase the production of patchouli oil is to ensure that the soil as a patchouli planting medium contains enough organic material.

The results of research conducted by [2] showed that patchouli will have PA value (Patchouli Alcohol) and higher oil content if planted in soil media containing 75% organic matter and the remaining 25% consists of NPK nutrients (nitrogen, phosphorus, potassium). Recent methodologies to find out the quantity of soil organic matter are elemental analysis coupled to Isotope ratio mass spectrometry (EA-IRMS), pyrolysis-gas chromatography coupled to mass spectrometry (Py-GCMS), and nuclear magnetic resonance spectroscopy (NMR) [3]. But this soil analysis method requires chemicals that are quite expensive, a long time laboratory analisys, and a process that is not easy. Some studies show that identification of soil nutrients can be done using an image.

Research conducted by Sagar More, et al. use soil chromatogram images to detect soil nutrients based on soil patterns and colors [4]. This study produced new features extracted from the chromatogram image [4]. Other studies have used imaging spectroscopy to measure the content of organic matter and nitrogen in the soil. The results of this study indicate that spectroscopy image can be used to measure and characterize spatial variability of carbon organic soil and nitrogen at the soil aggregate scale [5].

The use of imagery also provides optimal results for various studies in addition to identifying soil nutrient content. The use of satellite image data was carried out by [5] to identify patchouli plants based on histogram and Improved K_Means features. Another study uses imagery data of Unmanned Aerial Vehicle (UAV), texture features and Support Vector Machine (SVM) to identify Citronella plants. The results showed that the method used could identify citronella plants with accuracy reaching 94.23% with a Kappa value of 88.48% [6].

Research that utilizes imagery is also used to identify rice varieties based on the color and texture of rice using image processing and Artificial Neural Networks. The use of color parameters resulted in an accuracy of 54.83%, the use of texture parameters resulted in an accuracy of 100%, and the use of combination parameters (color and texture) resulted in an accuracy of 97.92% [7].

Based on the success of previous research using image data, this study utilizes the soil images taken with DLSR camera to identify soil organic matter content. The observations indicate that the soil containing high organic matter has a different color and texture than other types of soil. Basically, the color of the soil shows an indicator of the quantity of organic material, drainage and aeration [4]. Therefore, we choose these two features information as input in the identification process. Besides, the study show that the color features and texture features are quite effective to be used in the recognition process [8] [9] [10].

In this study, we extract color features using color moment and extract texture features using the Gray Level Co-occurrence Matrix (GLCM) method. GLCM is a method that is quite effective used for texture analysis [11], where the advantages are in the use of angles in the calculation process [12]. For the classification, this study uses Backpropagation Neural Networks. Based on the description of previous research, Backpropagation proved effective for the prediction process [8]. The use of Backpropagation Neural Network caried out by [9] to identify the nutritional status of nitrogen and potassium on leaf of mustard green plants produced accuracy of 97.82% for nitrogen and 78.70% for mustard leaves [9].

2 Teory Review of Soil Image Feature and Existing Method

2.1 Determining Soil Image Features Based on Soil Physical Properties

Patchouli (Pogostemon Cablin Bent) is a group of essential oil-producing plants. Patchouli can grow well on soil with the following conditions [13]:

a. The type of soil is Regosol, Red Latosol or Aluviall.
b. The soil structure is loose and deep, fertile and contains a lot of organic matter.
c. Soil texture is sandy clay or dusty clay.

Organic matter is a small part of the soil which consists of plants or animals that have undergone decomposition [14]. The definition of soil organic matter in the broadest sense includes all organic matter found in the soil regardless of its origin or decomposition state [15]. Based on these growth conditions for patchouli, this study selected several land properties that are related to the content of organic matter and can be identified using soil imagery. The properties include soil color, soil texture and soil structure.

Soil color can be used as an indication of the quantity of soil organic matter, where the darker the color of the soil, the higher the content of organic matter. Certain methods are needed to extract color features based on the color degradation of the soil image. This study uses color moments for color feature extraction.

Physical properties of soil that can be used as an indication of soil fertility include soil texture and soil structure [16]. Soil texture shows a relative comparison of sand, dust and clay fractions, each of which has a different size. The United States Department of Agriculture (USDA) divides the soil texture into 3 general textures, namely sandy land, clay soil and muddy soil. Soil structure is the arrangement of primary soil particles (sand, dust, and clay) to aggregates. These two physical properties mainly use soil particles from large (rough) to small (fine) sizes. In this study, both physical properties of soil were extracted from soil images as texture features by using GLCM.

Center for Soil and Agroclimate Research, Bogor, Indonesia classifies the quantity of soil organic matter in several criteria. Criteria for organic matter based on organic matter content can be seen in Table 1. These five criteria are then used as class references in the process of classifying the quantity of soil organic matter.

Table 1. Criteria of organic matter

Organic Matter (%)	**Criteria**
< 1,00	Very Low
1,00 – 2,00	Low
2,10 – 4,20	Moderate
4,30 – 6,00	High
> 6,00	Very High

2.2 Review of Existing Method for Feature Extraction and Classification

2.2.1 Color Moment

Color Moments is a method for extracting color features of an image. This method is able to extract features without being influenced by differences in lighting and image size [6], making it very effective for analyzing images based on color [10]. This study uses two color moments namely the mean and standard deviation. The formula for the mean is shown in equation 1 and the formula for the standard deviation is shown in equation 2.

$$\mu_c = \frac{1}{M\,N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} P_{i,j}^{c} \tag{1}$$

$$\sigma_c = \left[\frac{1}{M\,N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (P_{i,j}^{c} - \mu_c)^2 \right]^{1/2} \tag{2}$$

Where μ is the mean value, c is the color component, $(P_{i,j}^{c}$ is the pixel value (i, j) in the color component c, M is the height of the image, N is the width of the image and σ is the standard deviation.

2.2.2. Gray Level Co-occurrence Matrix (GLCM)

GLCM is a statistical feature-based extraction method. The characteristics are obtained from the pixel value of the matrix, which has a certain value and forms an angle of pattern. The angles formed by using GLCM are 0, 45, 90, and 135. Based on research conducted by [12], texture feature extraction using the GLCM method has high discrimination accuracy and fast calculation time, so it is efficiently used for real time pattern recognition applications [17].

There are fourteen texture features measured from the probability matrix to extract the statistical characteristics of the texture of remote sensing images [12]. In this study, the texture features extracted are Angular Second Moment (ASM), Contrast, Correlation, Inverse Difference Moment (IDM), and Entropy.

a. Angular Second Moment (ASM)

ASM also called Uniformity or Energy, is the number of squares of entries in GLCM to measure the homogeneity of an image. ASM has high value when the image has excellent homogeneity. The formula for ASM is shown in equation 3.

$$ASM = \sum_{i,j=0}^{N-1} \{p(i,j)\}^2 \tag{3}$$

b. Contrast

Contrast is the spatial frequency of the image and the difference in the GLCM moment. The difference is the difference in height and low pixel. Contrast will be 0 if the neighbor pixel has the same value. The contrast formula is shown in equation 4.

$$Contrast = \sum_{i,j=0}^{N-1} p_{i,j} (i-j)^2 \tag{4}$$

c. Correlation

Correlations are used to measure the linear dependence of the gray level of neighboring pixels. Correlations can be calculated using equation 5.

$$Correlation = \frac{\sum_{i,j=1}^{N} (i,j)(GLCM(i,j) - \mu_i\,\mu_j)}{\sigma_i\,\sigma_j} \tag{5}$$

d. Inverse Difference Moment (IDM)

IDM is a local homogeneity. IDM will be high when the gray level is uniform and inverse of GLCM is high. IDM can be calculated using equation 6.

$$IDM = \sum_{i,j=0}^{N-1} \frac{p(i,j)}{1+(i-j)^2} \tag{6}$$

e. Entropy

Entropy measures the loss of information or messages in the transmitted signal and also measures image information. Entropy can be calculated using equation 7.

$$Entropy = -\sum_{i,j=0}^{N-1} p(i,j)\log\{p(i,j)\} \quad (7)$$

2.2.3 Backpropagation Neural Network

Artificial Neural Network (ANN) is an information processing system designed to mimic the workings of the human brain in solving problems. One ANN method is Backpropagation. This method is very good in dealing with the problem of recognizing the complex patterns such as data compression, detection of computer viruses, object identification, sound synthesis from text and others.

The Backpropagation algorithm has three basic stages, namely forward propagation, backward propagation, and weight adjusting [16]. Forward propagation is related to training input values, while backward propagation is related to error. The training process of backpropagation is as follows:

Initial Initialization

If the epoch value is less than the epoch maximum and the MSE value is greater than the target error value, then do the following steps for each pair of nodes on the network.

Phase Fase I: Forward propagation

Each input node receives an input signal xi and then it is sent to the hidden layer.
Each node in the hidden layer summarizes the weighted input signal using equation 8.

$$Z_{inj} = v_{oj} + \sum_{i=1}^{n} x_i v_{ij} \quad (8)$$

Activation function for the output value is calculated using equation 9.

$$Z_j = f(Z_{inj}) = \frac{1}{1+e^{-Zinj}} \quad (9)$$

Each node in the output layer summarizes the weighted input signal using equation 10.

$$Y_{ink} = w_{ok} + \sum_{j=1}^{p} z_j w_{jk} \quad (10)$$

Activation function to calculate the output value using equation 11

$$Y_k = f(Y_{in}) = \frac{1}{1+e^{-Yink}} \quad (11)$$

Phase II: Backward Propagation

Calculation of error values uses equation 12.

$$\delta_k = (t_k - Y_k)Y_k(1 - Y_k) \quad (12)$$

Calculate the weight correction value by equation 13.

$$\Delta w_{jk} = \alpha \delta_k z_j \quad (13)$$

Calculate the bias correction value by equation 14.

$$\Delta w_{0k} = \alpha \delta_k \tag{14}$$

Every node in the hidden layer is summed by delta unit sum:

$$\delta_{inj} = \sum_{k=1}^{m} \delta_k w_{jk} \tag{15}$$

Calculate the error value .

$$\delta_j = \delta_{inj}(z_j)(1 - z_j) \tag{16}$$

Calculate weight correction value:

$$\Delta v_{ij} = \alpha \delta_j x_i \tag{17}$$

Calculate the bias correction value:

$$\Delta v_{0j} = \alpha \delta_j \tag{18}$$

Each output layer node corrects the weight value and the bias value with equations 19 and 20.

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \tag{19}$$

$$w_{0k}(new) = w_{0k}(old) + \Delta w_{0k} \tag{20}$$

Each node in the hidden layer also repairs the weights and bias values with equations 21 and 22.

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij} \tag{21}$$

$$v_{0j}(new) = v_{0j}(old) + \Delta v_{0j} \tag{22}$$

2.2.4 Normalization and Denormalization Data

Data normalization is a process of scaling data so that the data is in a certain range of values. This study uses normalized data as the input of identification process. Furthermore, the output value has been obtained from the system is denormalized to obtain the actual value. The equations for normalization and denormalization are shown in equations (24) and (25) respectively.

$$y = \frac{x - \min}{\max - \min} * 0{,}8 + 0{,}1 \tag{24}$$

$$y' = \frac{x' - 0{,}1}{0{,}8}(\max - \min) + \min \tag{25}$$

Where y is normalized data, y' is denormalized data, x is data before normalization, x' is data before denormalization, max is the biggest data value and min is the smallest data value.

2.2.5 Nguyen-Widrow Algorithm

Nguyen-Widrow is an algorithm that is used for initialization and generation of initial weights in the training of neural networks. The steps of this algorithm are as follows:

1. Inisalization of weight in range (-0,5) to 0,5
2. Calculate the value $\|v_{ij}\|$ by using equation 26.

$$\|v_{ij}\| = \sqrt{v^2{}_{1j} + v^2{}_{2j} + \cdots + v^2{}_{nj}} \quad (26)$$

3. Calculate the scale factor (β) by using equation 27.

$$\beta = 0{,}7(p)^{1/n} = 0{,}7\sqrt[n]{p} \quad (27)$$

Where n is the number of input and p is the number of hidden unit.

4. Calculate the value of v_{ij} by using equation 28.

$$v_{ij} = \frac{\beta v_{ij}(lama)}{\|v_{ij}\|} \quad (28)$$

Initialize bias weight in range (-β) to β

2.2.6 Mean Square Error (MSE)

Mean Square Error (MSE) is a method for evaluating errors. MSE can be calculated using equation 29.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2 \quad (29)$$

Where N is the number of data, y_i is output data (prediction), and t_i is the target data.

3 Method

3.1 Data Preparation

The steps of data collection in this study include the observation stage, soil image taking and laboratory analysis.

Research observations were carried out under the guidance and supervision of agricultural experts. Observations are made by taking soil samples for training data and testing data. The collection of soil samples must be in a location that has the same parent soil material. In this study the locations used for observation were the central Blitar Regency, namely in the districts of Kanigoro, Kesamben, Wlingi, Selopuro, Selorejo, Wonodadi, Srengat, Garum, Sanankulon, Kanigoro, and Sutojayan.

The soil that becomes the sample data is stored as an image before laboratory analysis. This study takes images in two soil conditions, namely wet and dry to determine the best soil conditions for input image. Steps for taking soil imagery are explained as follows:

1. The soil in wet or dry conditions is placed in a mini studio box with a 25 Watt lamp illumination from the side of the box.
2. Taking the soil image from the top side of the mini studio uses DSLR camera.
3. Next, soil image is cropped with a size of 300x300 pixels to be used as training data. As for the test data using the original image size.

Data of soil samples are then tested in the laboratory to analyze the quantity of organic material. Based on the interview with the expert, the soil for laboratory analysis purposes must be dried first to eliminate the quantity of water in the soil. Soil is placed in a room where sunlight cannot enter the room for two days. This is done in order to eliminate the quantity of water without damaging the quantity of soil c-organic matter. Laboratory analysis results are used as validation data of the calculation results obtained from the system.

3.2 Process Flow

The flow chart for the identification of the quality of organic materials is shown in Fig. 1. Soil image as input of this process has size 300x300 pixels. The input is then processed using several stages, namely the color feature extraction stage using the color moment, texture feature extraction using the gray level co-occurrence matrix (GLCM), learning phase, and testing phase. The output of this process is the class of the quantity of organic matter referring to the classification in Table 1.

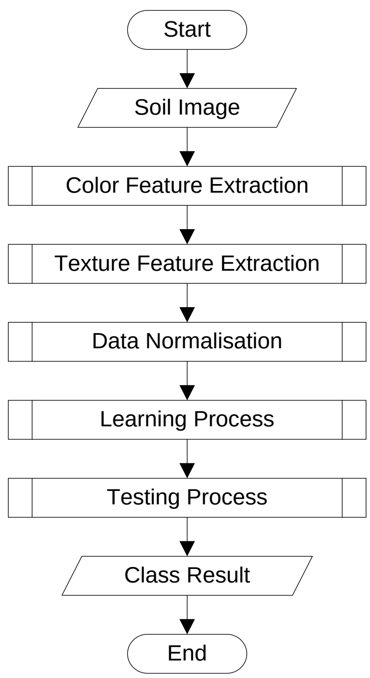

Fig. 1 Process Flow

The calculation of color moment features is done on each RGB color component. The calculation of the GLCM feature is also performed on each RGB color component using 5 texture features (ASM, contrast, correlation, IDM and entropy) and at 4 angles (0, 45, 90 and 135). Feature extraction process produces 6 color features for each color and 60 texture features for 4 GLCM angles. These features are then used as input to the learning and testing process using BPNN.

The learning process of Backpropagation NN follows three stages, namely forward propagation, backward propagation, and weight adjusting. The initial weight in the learning process is calculated using the Nguyen Widrow algorithm. The learning process is done to obtain the best combination of parameters and the best weight which is then used as a reference in the testing process. The testing process of Backpropagation NN uses only the forward propagation stage and the end result is a class of quantity of organic matter.

The network architecture of BPNN used in this study is shown in Fig. 2. The maximum number of input neurons is 66 which relates to the amount of color feature and texture features extraction. This study tested the most optimal feature combination for the process of identifying the quantity of soil organic matter, so that the number of input neuron follows the number of combinations of features to be tested. The number of output neurons is one which is the result of the classification of the quantity of soil organic matter. The soil organic matter classes consist of very low, low, medium, high and very high.

Determining the number of hidden layer layers and the number of neurons in the hidden layer using Heaton rules. Based on these rules, the number of hidden layer layers used is one, and the number of neurons in the hidden layer layer is 2/3 of the number of inputs plus the number of outputs, so the number of neurons in the hidden layer is 45.

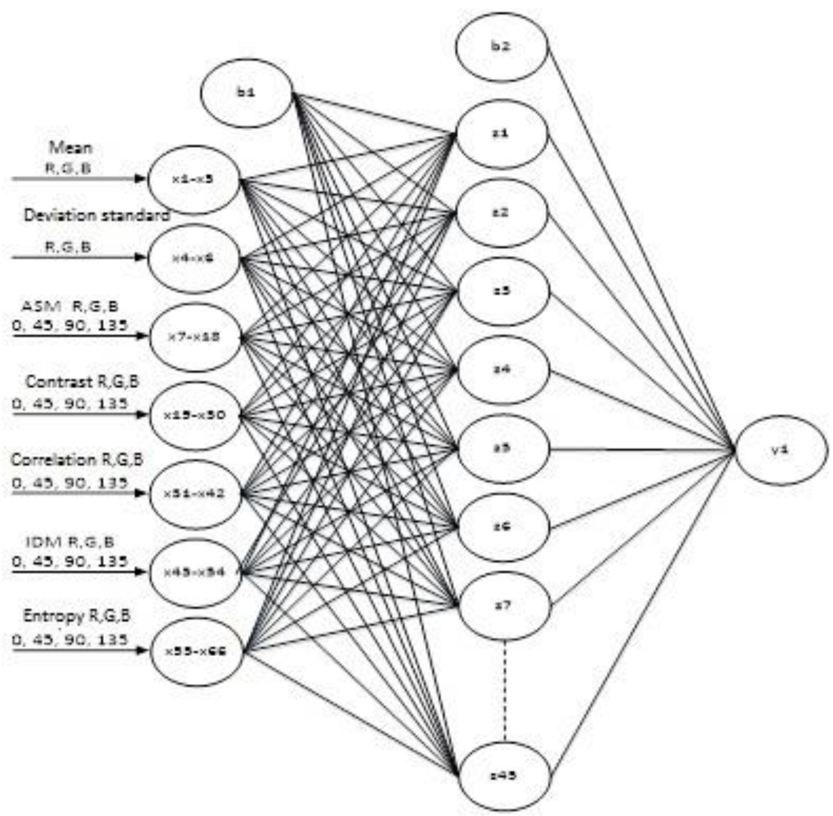

Fig. 2 Backpropagation neural network architecture

4 Result and Discussion

This study conducted several experiments, namely:

1. Experiment of the uses of input images taken in wet and dry soil conditions.
2. Experiment to get the best BPNN parameters which includes testing the maximum number of iterations, learning rates and the number of training data.
3. Experiment of the uses of the combination of GLCM features and the combination of GLCM features with color features

This experiment uses a total of 210 training data and 12 test data. The initial weight value of BPNN for each experiment was calculated by the Nguyen-widrow method. The following are the results and analysis of the tests performed.

4.1 The Experiment of Soil Image

There are two soil images tested, namely the soil image taken in wet soil conditions and the soil image taken in dry soil conditions. This test was conducted to find out better soil conditions for image data to be taken and then used as input in the next testing phase. For this experiment, we uses 210 traing data, 12 testing data, the maximum iteration of 500, and a learning rate of 0.3.

The test results of using the images input taken in wet soil condition and dry soil conditions to the level of accuracy and MSE can be seen in Table 2.

Table 2 Result testing of soil condition

Soil Condition	Accuracy	MSE
Wet	46%	0,7782
Dry	38%	1,0604

Based on Table 2 it can be seen that soil image taken in wet soil conditions results in higher accuracy and lower MSE values than dry soil conditions. Therefore, the data for further testing use images taken in wet soil conditions.

4.2 The Experiment of Maximum Iteration

The maximum iteration test results on the level of accuracy and MSE can be seen in Table 3.

Table 3 result testing of maximum iteration

Maximum Iteration	Accuracy	MSE
100	27%	1,302
200	23%	1,0798
300	28%	0,8924
400	33%	0,814
500	46%	0,7782
600	50%	0,7522
700	43%	0,729
800	43%	0,7052
900	51%	0,6946
1000	56%	0,6858

Based on Table 3 it can be seen that the maximum iteration value of 1000 produces the highest accuracy and the lowest MSE value.The greater the maximum iteration value, the process of training of Backpropagation neural networks also requires more time. In each iteration process there is an improvement of errors that occurred in the previous iteration.

4.3 The Experiment of Learning Rate

Learning rate testing results on the level of accuracy and MSE can be seen in Table 4. Small learning rate valuesrequire longer iterations to achieve high accuracy. The larger learning rate with the same iteration value will result in higher accuracy. But, if the learning rate is too large, it will cause unstable training. Based on Table 4 it can be seen that the optimal value in order to obtain the highest accuracy at learning rate is 0.5 with an average accuracy of 65% and an MSE value of 0.674.

Tabel 4 Result testing of learning rate

Learning Rate	**Accuracy**	**MSE**
0,01	41%	0,9398
0,03	48%	0,965
0,05	35%	0,7812
0,07	35%	0,681
0,09	33%	0,6816
0,1	41%	0,676
0,3	56%	0,6858
0,5	65%	0,674
0,7	63%	0,716
0,9	58%	0,6758

4.4 The Experiment of The Number of Training Data

In general, a large amount of training data will result in higher accuracy. But with a small amount of training data it can also produce high accuracy if we have better data quality. The results of testing for the amount of training data on the level of accuracy and MSE can be seen in Table 5. Based on Table 5 it is known that the number of training data with the best results is 210.

Tabel 5 Result testing of the amount of learning data

Number of Learnig Data	**Accuracy**	**MSE**
210	65%	0,674
180	61%	0,6542
150	60%	0,574
120	48%	0,5592
90	51%	1,0618
60	53%	0,9366
30	50%	0,619
15	50%	0,7086

4.5 The Experiment of GLCM Feature Combination

GLCM features on the level of accuracy and MSE can be seen in Table 6. Based on Table 6 it can be seen that the highest accuracy and the lowest MSE is produced by a combination of five GLCM features.

The ASM feature in GLCM is related to image homogeneity. ASM will produce high values if the image has good homogeneity. While the correlation feature is related to linear dependence from the gray level of neighboring pixels. The contrast feature is related to the distribution of pixels into color intensity. The IDM feature in GLCM will be high when the gray level of the uniform and inverse image of GLCM is high. While entropy is a feature that measures the loss of information or messages in the transmitted signal and measures image information.

Tabel 6 Result testing of GLCM feature combination

Feature Combination	**Accuracy**	**MSE**
Combination1	38%	0,7336
Combination2	38%	0,7774
Combination3	43%	1,019
Combination4	38%	0,8516
Combination5	35%	1,0596
Combination6	31%	1,0914
Combination7	43%	0,8274
Combination8	39%	0,8878
Combination9	33%	1,079
Combination10	50%	0,9548
Combination11	33%	0,8786
Combination12	36%	0,7718
Combination13	56%	0,6006
Combination14	35%	1,1282
Combination15	73%	0,5122

Combination description:

Combination1: ASM; Combination2: contrast; Combination3: correlation; Combination4: IDM; Combination5: entropy; Combination6: correlation and ASM; Combination7: correlation and contrast; Combination8: correlation and IDM; Combination9: correlation and entropy; Combination10: correlation, contrast and ASM; Combination11: correlation, contrast and IDM; Combination12: correlation, contrast and entropy; Combination13: correlation, contrast, ASM and IDM; Combination14: correlation, contrast, ASM and entropy; Combination15: correlation, contrast, ASM, IDM, and entropy

The next experiment combine five GLCM features with the color moment feature, namely the mean and standard deviation (STD). The result of experiment can be seen in Table 7.

Tabel 7 Result testing of GLCM feature and color moment

Feature Combination	Accuracy	MSE
GLCM	73%	0,5122
GLCM - *Mean*	73%	0,6868
GLCM - STD	51%	0,5152
GLCM - *Mean* – STD	70%	0,6692

Table 7 shows the highest accuracy is 73% obtained from a combining five GLCM features and from combination of GLCM features with mean features. But the combination of five GLCM features produces a smaller MSE value compared to the MSE value generated from a combination of GLCM features and mean.

These results indicate that the use of color moment in this case is not optimal. As already explained that the advantages of color moment is to extract color features without being affected by the difference in lighting problems. Whereas in this study, image data retrieval is done using a mini studio and used the same level of lighting. So that the use of the color moment feature does not provide better accuracy. Therefore, to get optimal results, the best features used is a combination of five GLCM features (ASM, contrast, correlation, IDM, and entropy)

5 Conclusion

This study uses color moment to extract color feature and GLCM to extract texture features as an input of Backpropagation Neural Network (BPNN) to determine the quantity of soil organic matter. To improve BPNN performance at the learning stage, we perform the Nguyen-Widrow method to determine the initial weight of the BPNN. The final weight obtained from the learning process is then used in the testing process. Accuracy resulting from the test is obtained from the percentage of the results of the test data in accordance with the target.

The experiment result shows the highest accuracy is 73%. This accuracy is obtained from testing using 5 GLCM features (ASM, contrast, correlation, IDM and entropy) and testing using a combination of 5 GLCM features with the Mean feature. However, the use of the 5 features of the GLCM gives a smaller MSE value of 0.5122. This means that the use of the 5 GLCM features can be used without being combined with color features

The test results also showed that the highest accuracy was obtained during the experiment using the number of training data of 210, the test data of 12 and the number of hidden neurons of 41. The learning rate used is 0.5 and the maximum iteration is 1000. The results of the identification of the quantity of soil organic matter through the image produces a higher accuracy if using the image data taken in wet soil conditions.

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