# NPK Soil Nutrient Measurement Prototype Based on Local Binary Pattern And Back-Propagation

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***Abstract*— Nutrient elements of NPK are macro nutrients that play an important role in the growth and development of plants, therefore it is necessary to measure NPK nutrient content to measure how well soil fertility condition before the land planting period, but NPK measurement through laboratory tests takes a relatively long time. This research develops a prototype of NPK nutrient measurement system based on a mobile application by using soil image for determining the textural characteristic, the textural characteristics are processed with local binary pattern and back-propagation neural network to accelerate the measurement process.**

**Sample data in this research was taken on rice field land in the province of Yogyakarta Special Region by varying the distance at 30 cm to 110 cm with interval 20 cm and angle image capture at -30° to 30° with interval 10°. Datasets were being pre-processed to improve image quality and adjust image format. Preprocessed results are extracted using local binary pattern uniform to obtain texture features. The texture features were being inputted of the neural network model, that being trained with a back-propagation algorithm by varying parameters of the neural network model.**

**The model tested to determine the effect of distance and angle of image capture, system processing speed, and effect of artificial neural network parameters. The best model is implemented on a smartphone application. The results obtained an average of computation time 0.65s, and the optimal result is obtained at distance capture of 50 cm and angle capture of 0° with the measurement accuracy at each soil nutrient level of nitrogen 91.80%, while phosphorus 83.49%, and potassium 82.54%, therefore the average is 84.16%**

***Keywords*— *smartphone, texture features, NPK soil nutrient***

## I. INTRODUCTION

Soil nutrients such as nitrogen, phosphorus, and potassium (NPK) play an important role in the growth and development of the plant. Each Plant has a certain composition to achieve their optimal growth and development. Therefore, soil fertility conditions should be checked periodically, so that fertilization process runs optimally, and keep maintaining the condition of soil fertility. On the other hand, the laboratory requires a lot of time and cost, which can incriminate farmers in both cost and time. NPK nutrient testing in the laboratory can take up to one to two months. The time can be influenced by other factors such as queue length and number of samples to be tested, so much time is wasted, therefore a measurement system is needed that can know the nutrient content of NPK quickly.

The soil is a complex material that varies in terms of physical, biological, and chemical elements [1]. Variations in physical terms such as texture and soil color can certainly be a distinctive feature that distinguishes one land from another. Methods such as image processing are utilized in a variety of fields, one of which is in research [2], which utilizes to classify white blood cells, as well as research [3], which utilizes to detect car parking space. In addition, research on digital image processing and artificial neural networks is also implemented on smartphones such as optical character recognition (OCR) for text to speech. Digital image processing certainly requires an image acquisition device, while artificial neural networks require considerable computing devices, therefore smartphones can be an alternative that accommodates those terms. Today, computing power and camera quality of smartphones continue to grow, allowing it to run digital image processing algorithms and artificial neural networks in smartphone applications.

Local binary pattern (LBP) and artificial neural networks were used to develop vehicle classifier model [5]. LBP operation is one extracting texture traits with efficient computation, utilizing the difference between pixels and its neighbors [6]. According to the study [7], LBP obtained higher accuracy result when compared to gray level co-occurrence matrix (GLCM) in extracting texture features in acute lymphocytic leukemia. The LBP operation works by comparing the middle pixel value with its neighboring pixel value so that if there is a change in the light intensity evenly the value of the feature will be the same.

## II. METHODOLOGY

The research proses consist of gathering soil image dataset, preprocessing, feature extraction, and training the neural network model with the backpropagation algorithm. Fig. 1 shows the research process block diagram, which details explained as follows.

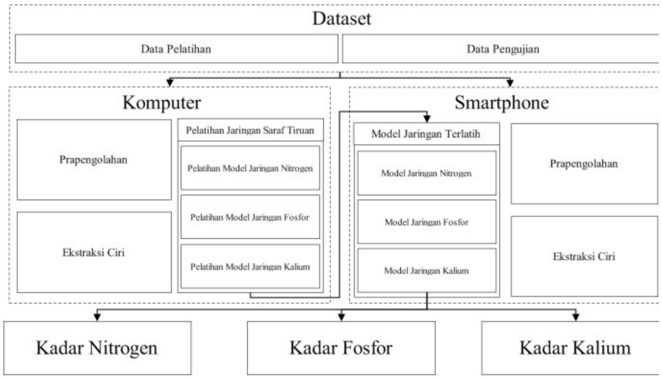


Fig. 1. Research Block Process

### *A. Preprocessing*

Preprocessing is done to improve image quality and adjust image format for further processing. Variations of light illumination can affect the feature extraction results, to eliminate light illumination factors, it is necessary to normalize light intensity using histogram equalization [8]. After preprocessing, data can be more reliable in a variety of conditions, and it has a certain equivalent resolution among different smartphone devices. There are several preprocessing stages were used in this research, the first stage was cropping image data to take the region of interest (ROI) of 640 x 480 pixels, and image data format were converted into the grayscale format. Histogram equalization process is used to normalize the image pixel value, while the noise reduction is done by Gaussian blur.

### *B. Feature Extraction*

Local binary pattern uniform (LBPU) operator were used to extract texture feature from soil image data. The working principle of local binary pattern uniform is comparing middle pixel value with it’s neighbors, in this example results will be encoded into 8-bit as shown in Fig. 2, and replace the old pixel value with the decimal value of the 8-bit encoding, the last process made histogram of uniform and non-uniform pattern to produce 59 texture features [9,10]. Uniform pattern for 8-bit value has decimal value U = {0, 1, 2, 3, 4, 6, 7, 8, 12, 14, 15, 16, 24, 28, 30, 31, 32, 48, 56 , 60, 62, 63, 64, 96, 112, 120, 124, 126, 19, 193, 193, 193, 223 , 227, 231, 239, 240, 241, 243, 247, 248, 249, 251, 252, 253, 254 and 255}, while other decimal values are non-uniform patterns [10].

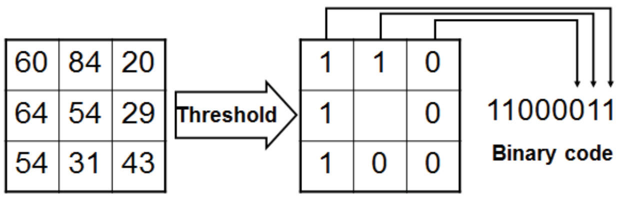


Fig. 2. Local Binary Pattern

### *C. Backpropagation*

The neural network model is trained using back-propagation algorithm. The back-propagation algorithm consists of three phases, the feed-forward phase, back-propagation phase, and weight change phase. Output value at feed-forward phase subtracted by the target value, error from the process is used to improve the weight of the neural network model [11]. In this research, there are three networks model, nitrogen model, phosphorus model, and potassium model. Each of neural network architecture consists 59 units in the input layer, 1 hidden layer with the number of units varied, and 1 output layer. Model evaluation value uses equation (1), the mean absolute percentage error (MAPE) [12], and the activation function used is the sigmoid function.

$$MAPE[\%] = \frac{1}{N}\sum_{1}^{i}\frac{|P_A^i - P_p^i|}{P_A^i}\,X\,100 \qquad (1)$$

Where $P_A^i$ and $P_p^i$ are representations of the actual values and predictive values, whereas *N* and *i* represent the amount of total data and data index.

### *D. Dataset*

Dataset was taken on rice field area in Special Region of Yogyakarta, as presented in Table I. All of 10 samples data were taken at the range of light intensity 7500 - 25000 lux. The process of taking the image data of the soil is preceded by removing the outermost layer of soil, so that the layer meets the recommendations of the soil in humid conditions, for example as in Fig. 3. Dataset used as training model, then it is necessary for dataset to simulate the possibility of altitude and angle variation by image capture from user, while maintaining texture detail of the soil image data, so image data were taken at height 30 - 110 cm and the image capture angle in the range of -30 ° to 30 °, as well as variations at altitude with interval of 20 cm to see the characteristics of the system against the altitude of the image taking, and at each varied by 10 ° intervals to see the system characteristics of the image capture angle.

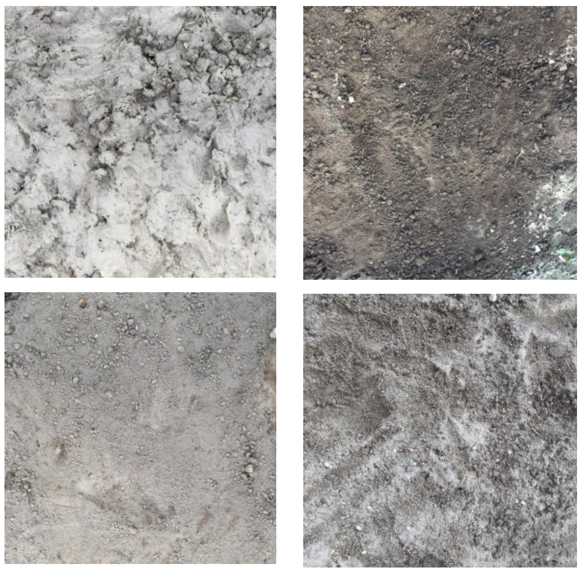

Fig. 3. Sample of image of the soil

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TABLE I. SAMPLE LOCATION

| No. | Place Name | Coordinate |
|---|---|---|
| 1. | Taman Tirto | 7°49'38.1"S 110°19'10.7"E |
| 2. | Kalasan | 7°46'17.7"S 110°27'07.9"E |
| 3. | Godean | 7°46'36.4"S 110°19'18.6"E |
| 4. | Palagan | 7°43'32.8"S 110°22'29.0"E |
| 5. | Guwosari | 7°51'35.7"S 110°18'29.7"E |
| 6. | Imogiri | 7°55'42.5"S 110°24'50.0"E |
| 7. | Cangkringan | 7°37'47.2"S 110°25'31.7"E |
| 8. | Pakem | 7°40'08.0"S 110°25'14.6"E |
| 9. | Pogung | 7°45'29.6"S 110°22'29.0"E |
| 10. | Stadion Bantul | 7°52'53.9"S 110°22'06.2"E |

Train data were used to train artificial neural network models with parameter optimizations that produce the best predictions, on the other hand, test data were used to evaluate the trained model. The soil sample was taken by removing the outermost layer, and the sample was tested nutrient content in Soil Laboratory at Agricultural Faculty of Universitas Gadjah Mada. Laboratory results would be used as network model targets, as well as validation of trained network models.

## III. RESULT AND ANALYSIS

### A. *Height and Angle Variation*

Tests on variations in distance and angle of image capture to obtain network model at distance and angle with optimal mean absolute percentage error (MAPE). This test is divided into two parts, at first test with variations of height, while data on each distance variation at 0° angle, and second test angle variation is used data each angle variation with height which has the smallest error. The condition of the neural network parameters is made constant at epoch 80000, the learning rate by 0.1, and 30 hidden layer units.

The height variation test consisted of eight training data and two test data for each distance variation in image capture, Fig. 4 is the training result on the network model and shows a local binary pattern (LBP) can distinguish texture characteristics between one soil features with others, because MAPE value of training model is relatively small, under 5%. Test results can be seen in Fig. 5, where the variation of the model has an upward trend in the range of 50 cm to 110 cm, while at a height of 30 cm to 50 cm decreases. This is because of the height distance will reduce the detail of the texture features, whereas at a close-up distance it reduces the relationship information between pixels.

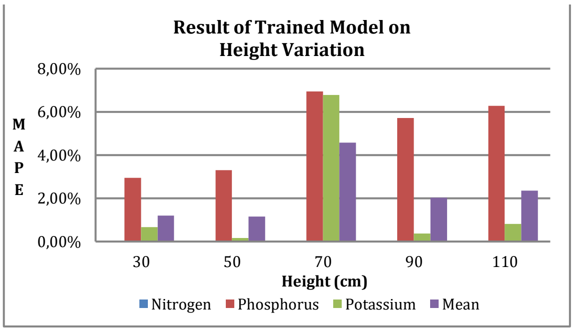


Fig. 4. The result of Trained Model on Height Variation

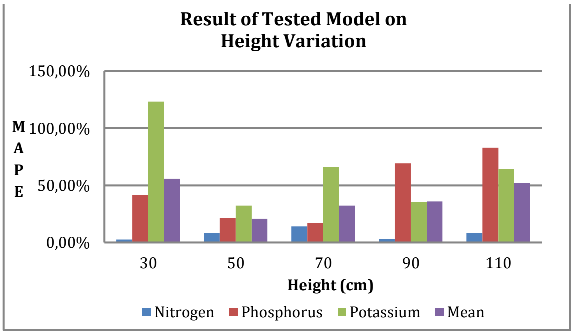


Fig. 5. The result of Tested Model on Height Variation

Test results on nitrogen nutrients have relatively small errors, one of the factors caused by the range of relatively small data, so that on the model with the sigmoid activation function, the results would be quite good.

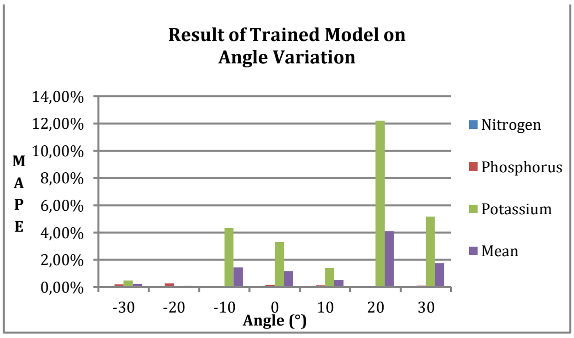


Fig. 6. The result of Trained Model on Angle Variation

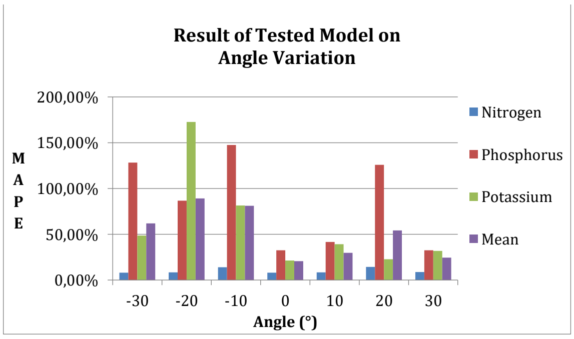


Fig. 7. The result of Tested Model on Angle Variation

Fig. 6 shows that LBP has a relatively lower MAPE value. The angle variations make the feature extracted by LBP quite discriminate texture features in the training. The test results presented in Fig. 7, show the MAPE value rising at an angle of 0 ° to 20 ° and 0 ° to -20 °, but at an angle of 20 ° to 30 ° and -20 ° to -30 ° MAPE value decreases. It is probably caused by a change in orientation that causes a change in the direction of the neighbor from the middle pixel, and the feature extraction using LBP is susceptible to changes in light intensity variations of which were not exhaustive, it is caused by image capturing angle, so the change of light is not equally distributed. Tests of each nutrient element obtained an optimum average measurement result at an angle of 0° with MAPE value of nitrogen content 8.20%, while phosphorus level 32.37%, and potassium level 21.43%, therefore the average was 20.67%.

## B. Neural Network Parameters

Tests on artificial neural network parameters were performed to optimize the neural network model parameters. The artificial neural network parameters to be tested are the number of epochs, the number the hidden layer unit, and learning rate, as shown in Table II This test uses data at 50 cm height and angle 0 ° with eight training data and two test data, it produces an optimal MAPE value on the test of height variation and angle image capture.

TABLE II. NEURAL NETWORKS PARAMETERS

| Parameter | Variasi |
|---|---|
| Epoch | 2500, 5000, 10000, 20000, 40000, dan 80000 |
| Hidden layer units | 10 unit, 20 unit, 30 unit, dan 59 unit |
| Learning rate | 0.001, 0.01, 0.1, 0.2, dan 0.4 |

Test on epoch variation is done by adjusting the constant value of learning rate 0.1 and 30 hidden layer units. Fig. 8 is the result of training accuracy on the epoch variation, the MAPE value has a decreasing trend when the epoch value is higher, it causes the weight value of the model closer to target value, but the MAPE value decrease in epoch to 40000 to 80000 is relatively sloping, it caused by error feedback to back-propagation is relatively small.

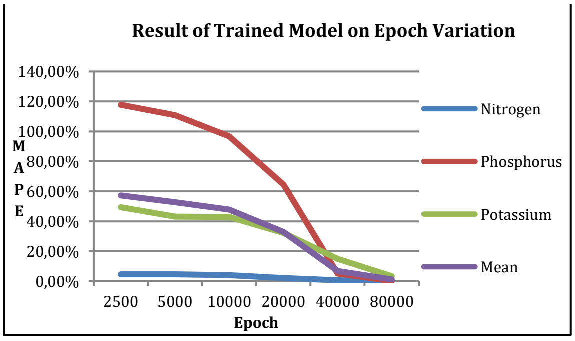


Fig. 8. The result of Trained Model on Epoch Variation

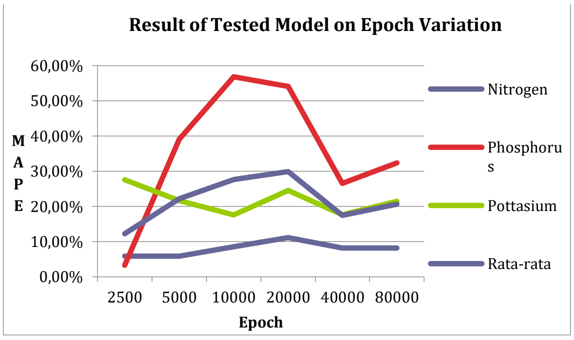


Fig. 9. The result of Tested Model on Epoch Variation

Unlike the case with the training results, the test model of the number of epoch has not determined whether the MAPE value would increase or decrease, as shown in Fig. 9. It is caused by over-fitting model, where the model undergoes excessive training that makes the network model equation so complex to fitting the train data, which may not necessarily represent all conditions. Another possibility that led to over-fitting model is that data used in training have a high bias or lack of sample data.

Test on the variations of the hidden layer unit was done by adjusting the neural network parameter by 80000 epochs with the learning rate value at 0.1. The results of the model training presented in Fig. 10, the results show the variation of the number of hidden layers in 10 units up to 30 units have an average MAPE value tends to be stable with a value below 2.00%, while at 59 units there is a significant increase in MAPE value to 7.04% that's because the number of units in the network model affects the complexity of the model.

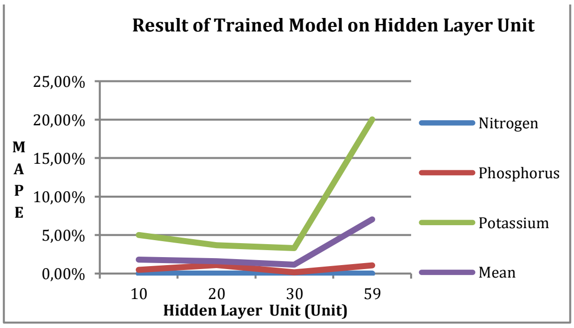


Fig. 10. The result of Trained Model on Hidden Layer Unit Variation

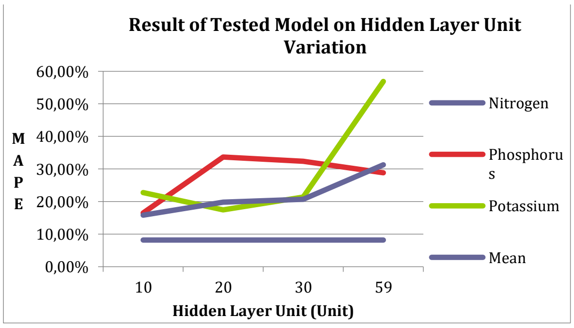


Fig. 11. The result of Tested Model on Hidden Layer Unit Variation

Unlike nitrogen model case having a stable MAPE value of 8.20%, due to number of units in the hidden layer determines computational speed and MAPE value of the variation of the number of hidden layer units in the same nitrogen network model, then for the nitrogen network model the number of hidden layer units which produces the optimum model of 10 units in the hidden layer, so that the number of units of each model is phosphorus (10 units), potassium (20 units), and nitrogen (10 units). The complexity of the model determines the amount of weight to be trained to achieve local/global minimum. Fig. 11 is the tested models, pulling trends from potassium and phosphor models tends to be the opposite.

Tests on learning rate parameters are performed to optimize the network model. Data test that was used at a distance of 50 cm with angle 0 °, on parameter 80000 epoch with the number in hidden layer units of potassium network model 20 units, while nitrogen and potassium levels 10 units. Fig. 12 can explain that too small learning rate would make propagation error in the back-propagation algorithm stuck at local minima.

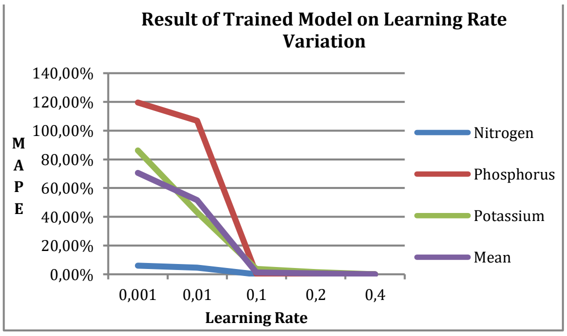


Fig. 12. The result of Trained Model on Learning Rate Variation

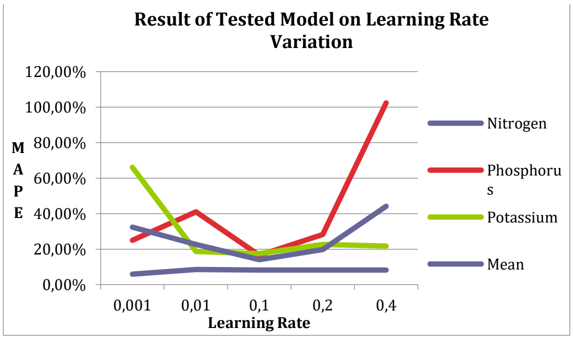


Fig. 13. The result of Tested Model on Learning Rate Variation

This happens because the feature extracted by LBP makes the model characteristics have small feedback that is used to change the weights, so the weight changed is not enough to pass local minima, therefore the weight value is changed around local minima. The result of the test model with the smallest error is at the 0.1 learning rate, overall, the highest accuracy model is at a distance of 50 cm and angle 0 ° with learning rate 0.1, epoch 80000, and 10 units for nitrogen network model 91.80% and phosphorus level 83.49%, while 20 units for potassium network model 82.54%, so the average is 84.16%, as shown in Fig. 13.

### C. *Process Time*

Computation time testing was done to determine the time required for the system initialization process, image processing, and feed-forward on artificial neural networks. Tests performed on smartphones with Exynos 7870 processors and 4GB RAM. Time calculation was done by pressing the photo button that will activate the logging function with output "status: start" and "status: stop". The difference between those times represents the computing time of the system, as can be seen in Table III.

The average computational time of the system model was under five seconds, so the process does not reach the application not responding status (ANR), while the result is 0.65 seconds. Computation time is quite fast due to the use of OpenCV libraries that are intended for computing in real-time, and the computational complexity of LBP was quite light.

TABLE III. PROCESS TIME

| No. Test | Process Time (second) | No. Test | Process Time (second) |
|---|---|---|---|
| **1** | 0.62 | **4** | 0.62 |
| **2** | 0.64 | **5** | 0.66 |
| **3** | 0.68 | **Mean** | 0.64 ±0.03 |

## IV. CONCLUSION

The conclusion that obtained that, this research successfully perform the measurement of NPK nutrient content with optimal height of 50 cm and angle 0 °. The established system were made by artificial neural network model parameters that yield the optimal value at the learning rate of 0.1, 80000 epoch, 10 units in the hidden layer for the nitrogen and phosphorus network model, while 20 units for the potassium network model, as for the average measurement accuracy for nitrogen level at 91.80%, while phosphorus level at 83.49%, and potassium 82.54%, therefore average was 84.16%. The system capable of measuring NPK nutrients at an average computational time of 0.64 seconds, making it very fast when compared with NPK nutrient content measurements using laboratory tests.

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