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SOIL QUALITY CLASSIFICATION WITH GRADIENT BOOSTING METHOD (CASE STUDY: PEANUT CULTIVATION)

Diah Kamalia*[1], Meidya Koeshardianto[2], Wahyudi Setiawan[3]
[1,2,3] Trunojoyo University of Madura, Madura, Indonesia
*Corresponding Author: diahkamelya@gmail.com

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Abstract*. This study aims to determine soil quality in peanut cultivation to support precise decision-making for farmers. Peanuts were selected due to their economic and nutritional importance in Madura, as well as their strong dependence on soil conditions. The research method used is the Gradient Boosting Classifier, utilizing four parameters: soil pH, soil moisture, air temperature, and air humidity. This method builds models iteratively by reducing errors from previous models by following the gradient movement towards the negative. The collected data are then processed through a classification approach to accurately determine soil suitability for peanut cultivation. The results indicate that the method can identify relationships among soil variables, making it a useful tool for predicting soil suitability for cultivation. The system is developed to enhance decision-making by enabling real-time soil condition monitoring with precision, improving soil management effectiveness, and optimizing sustainable and efficient cultivation practices for farmers in Buluh, Socah, Bangkalan.*

Abstrak: Penelitian ini bertujuan untuk menentukan kualitas tanah pada budidaya tanaman kacang tanah untuk pengambilan keputusan petani yang lebih presisi. Kacang tanah dipilih pada penelitian ini karena pentingnya kacang tanah secara ekonomi dan nutrisi di Madura, serta ketergantungannya yang kuat pada kondisi tanah. Metode penelitian yang digunakan adalah Gradient Boosting Classifier dengan memanfaatkan empat parameter seperti pH tanah, kelembaban tanah, suhu udara dan kelembaban udara. Metode ini membangun model secara iteratif dengan mengurangi error dari model sebelumnya ke arah gradien negatif. Data yang diperoleh akan dilakukan proses klasifikasi dengan menentukan kesesuaian lahan untuk budidaya tanaman kacang tanah yang akurat. Hasil penelitian ini menunjukkan bahwa metode yang digunakan mampu mengidentifikasi hubungan antar variabel tanah, sehingga dapat digunakan sebagai alat bantu untuk memprediksi kelayakan tanah untuk budidaya tanaman. Sistem ini dikembangkan untuk meningkatkan pengambilan keputusan dalam memahami kondisi tanah secara real-time, meningkatkan efektivitas pengolahan lahan untuk mengoptimalkan budidaya yang berkelanjutan dan efisien untuk para petani di kota Buluh, Socah, Bangkalan.

INTRODUCTION

Indonesia is widely referred to as an agricultural nation with massive agricultural lands. Agriculture plays a crucial role in meeting the Indonesian population's commodity needs (Ikhwali *et al.,* 2022). The country ranks as the fifth-largest peanut producer globally, following India, China, Nigeria, and Senegal. Between 1996 and 2000, the average production was 979,000 tons of peanuts annually, with a harvested area of 646,000 ha in total. Demand for peanuts in this country continues to rise, the average reaches 900,000 tons per year, with production reaching approximately 783,110 tons (87.01%) (Halim *et al.,* 2016). Peanut cultivation is widespread across districts or cities in Central Java mostly found in areas with moderate rainfall where peanuts are commonly planted after rice as a dry-season intercropping crop (Arianti *et al.,* 2021). Bangkalan Madura represents dry land in East Java. The extent of dry land is increasing during the dry season because water scarcity becomes more pronounced in some fields (Nurhidayati *et al.,* 2021). Water availability is a critical factor controlling both microbial activity and plant growth and controlled soil moisture conditions offer major advantages in agricultural experiments (Hill *et al.,* 1983). Rising in air temperature is likely to intensify the frequency and severity of heat stress during the peanut growing season in these regions (Parkash *et al.,* 2025). Additionally, maintaining the optimal soil pH is essential for maximizing peanut yield and quality, as it directly affects nutrient availability and plant health (Rusmayadi *&* Safruddin*,* 2024). High humidity also plays an important role in enhancing flowering, peg formation, and peg growth rates, which are linked to the growth regulator status of the developing fruit. (Lee *et al.,* 1972). These environmental factors are essential for farmers in determining land suitability for peanut cultivation, which ultimately impacts productivity (Rukmana *et al.,* 2019). Soil contains numerous macronutrients such as nitrogen, phosphorus and potassium. Deficiencies in these nutrients can lead to reduced soil infertility in plant growth (Fakhrezi *et al.,* 2023). Soil pH significantly impacts the nutrient uptake and fluctuations can hinder the absorption of key nutrients such as phosphorus and nitrogen, consequently affecting yield and crop quality. For peanuts, the ideal soil pH ranges from 5 to 6.3 (Sirait & Siahaan, 2019).

It is important to continuously monitor the parameters. However, conventional monitoring systems, which rely on human labor are often inefficient, costly, complex, and unable to visualize real-time data required (Rahman *et al.,* 2020). To address the inefficiency in peanut cultivation, Farmers can utilize precision agriculture technologies to collect data and make decisions to enhance productivity. Precision farming leads to modern approaches that leverage advanced technologies to optimize agricultural output (Neelakantan P, 2023). Artificial Intelligence (AI), a field within computer science, enables automation activities related to thinking processes, problem solving and learning (Zunali & Wahjono, 2022). Machine Learning, a subset of AI, allows users to analyze data structures, patterns and generate predictions from datasets (Zhou *et al.,* 2017).

Within Machine Learning, Data Mining is one of the methods which a combined technique from pattern recognition, statistics, databases, and visualization to extract meaningful data by retrieving information from large datasets (Larose & Larose, 2014). Generally, it is used to analyze data and identify relationships, trends or patterns that may not be immediately apparent, aiming to find extra value from a collection of data (Bramer, 2007). One of key applications of Data Mining is classification, a Supervised Learning approach used to predict categorical labels based on input features (Gorade *et al.,* 2017). Classification models are developed using sets of training data and testing data, where predictions are made by calculating similarities between new and existing data (Lukito & Chrismanto, 2015).

Effective data analysis plays a vital role in ensuring successful business operations (Chazal & Michel, 2021) for informed decision-making and improved outcomes. Among various data analysis approaches, classification stands out by employing categorization using both conventional statistical models and machine learning models (Kairupan *et al.,* 2023). One such method is the Gradient Boosting Classifier, an ensemble or a combination learning technique (Ismanto & Novalia, 2021) that combines several predictions of Decision Tree models commonly called weak learners into a more complex model. This method builds models iteratively, with each new weak learner correcting the errors of the previous one by following the gradient movement (towards the negative) of the loss function. Through this gradual error correction, the model's performance is enhanced over time. The number of iterations indicates the number of trees formed, this process continues until the model meets certain criteria (Nainggolan & Sinaga, 2023).

To achieve the optimal results, hyperparameter tuning is necessary. In the Gradient Boosting, key parameters include the number of trees (*n_estimators*), learning rate (*learning_rate*), and maximum tree depth (*max_depth*). The tuning process can significantly affect model performance, and also increase computational time as the number of parameters grows (Nugraha & Sasongko, 2022). This study employs the Grid Search method which systematically works by evaluating all possible parameter combinations to find the best value during the training phase (Dwirahmanto & Bisri, 2023).

This research aims to classify a real-time soil suitability for peanut cultivation using four parameters (soil Ph, soil temperature, humidity and temperature) that can be designed and deployed with the use of Gradient Boosting Classifier. This research was conducted in Buluh Village, Socah, Bangkalan. By analyzing soil characteristics, this research seeks to optimize fertilization, promote sustainable and efficient farming practices and examine significant differences in measurements across these locations.

METHOD

The workflow in this study consists of three main stages, data preprocessing, hyperparameter tuning and classification. The first stage in data preprocessing is data cleaning which is the process of removing noise in data including irrelevant data, inconsistent data and data containing errors (Zai, 2022). After the cleaning stage is complete, categorical data is transformed into numerical form (Nofriansyah, 2017). The next stage is to tune the parameters using Grid Search, this tuning process aims to provide the best parameter value from the used classification method. The parameters used in the tuning process are shown in Table 1.

Table 1. Hyperparameter for Tuning

Parameter	Range
learning_rate	0.15, 0.1, 0.05, 0.01, 0.005, 0.001
n_estimators	125, 150, 175, 200, 225, 250
max_depth	1, 3, 5, 7, 9

After the tuning process produces the best parameters, the next step is classification using the Gradient Boosting method, which is a classification method that is an ensemble or combination of Decision Tree. The output of this method is a tree which will be combined with a new tree in the next iteration depending on the number of the used trees *(n_estimators).* This method trains the model sequentially where the tree in the new iteration fixes the error or loss function of the previous tree. The Gradient Boosting method moves towards a negative gradient, the more iterations the more trees are formed that the error or loss function value will become smaller. The final prediction of the Gradient Boosting method is produced by accumulating the Predicted Residual value of each formed tree. The following text is an explanation of the classification stages using the Gradient Boosting method.

1. Calculating the *Initial Prediction*
$$\boldsymbol{I = log(odds) = log\left(\frac{P\ (Y=1)}{P\ (Y=0)}\right)}$$
2. Calculating *Predicted Probability*
$$\boldsymbol{L = \frac{e^{log(odds)}}{1+e^{log\ (odds)}} = \frac{e^{I}}{1+e^{I}}}$$
3. Calculating Residual Value
$$\boldsymbol{dL = y - L}$$
4. Forming Weak Learner (tree)
5. Calculating *Predicted Residual*
$$\gamma = \frac{\sum_{i=1}^{n} \boldsymbol{dL_i}}{\sum_{i=1}^{n}[\boldsymbol{L_i} \times (\boldsymbol{1} - \boldsymbol{L_i})]}$$
6. Calculating the prediction results
$$\boldsymbol{y_{prediction} = I + \alpha} \times \gamma$$
7. Forming a new Weak Learner (tree)
8. Combining Weak Learner (tree)
9. Calculating Final Prediction
$$\boldsymbol{F_{prediction} = I + \alpha \times \gamma_1 + \alpha \times \gamma_2 + \ldots . + \alpha \times \gamma_n}$$
10. Prediction Results

In this research, the list of performance measurement criteria for the classification model is accuracy, precision, sensitivity, specificity). The calculation of each of these criteria is shown in Table 2.

Table 2 Performance Measurement

Criteria	Formula
Accuracy	$\frac{(TP+TN)}{(TP+TN+FP+FN)}$
Precision	$\frac{TP}{(TP+FP)}$
Sensitivity	$\frac{TP}{(TP+FN)}$
Specificity	$\frac{TN}{(TN+FP)}$

1. *True Positive* (TP) is the amount of data that has a positive actual value and a positive predicted value.
2. *True Negative* (TN) is the amount of data that has a negative actual value and a negative predicted value.
3. *False Positive* (FP) is the amount of data that has a negative actual value and a positive predicted value.

4. *False Negative* (FN) is the amount of data that has a positive actual value and a negative predicted value.

The flowchart of the Gradient Boosting method can be seen in Figure 1 below.

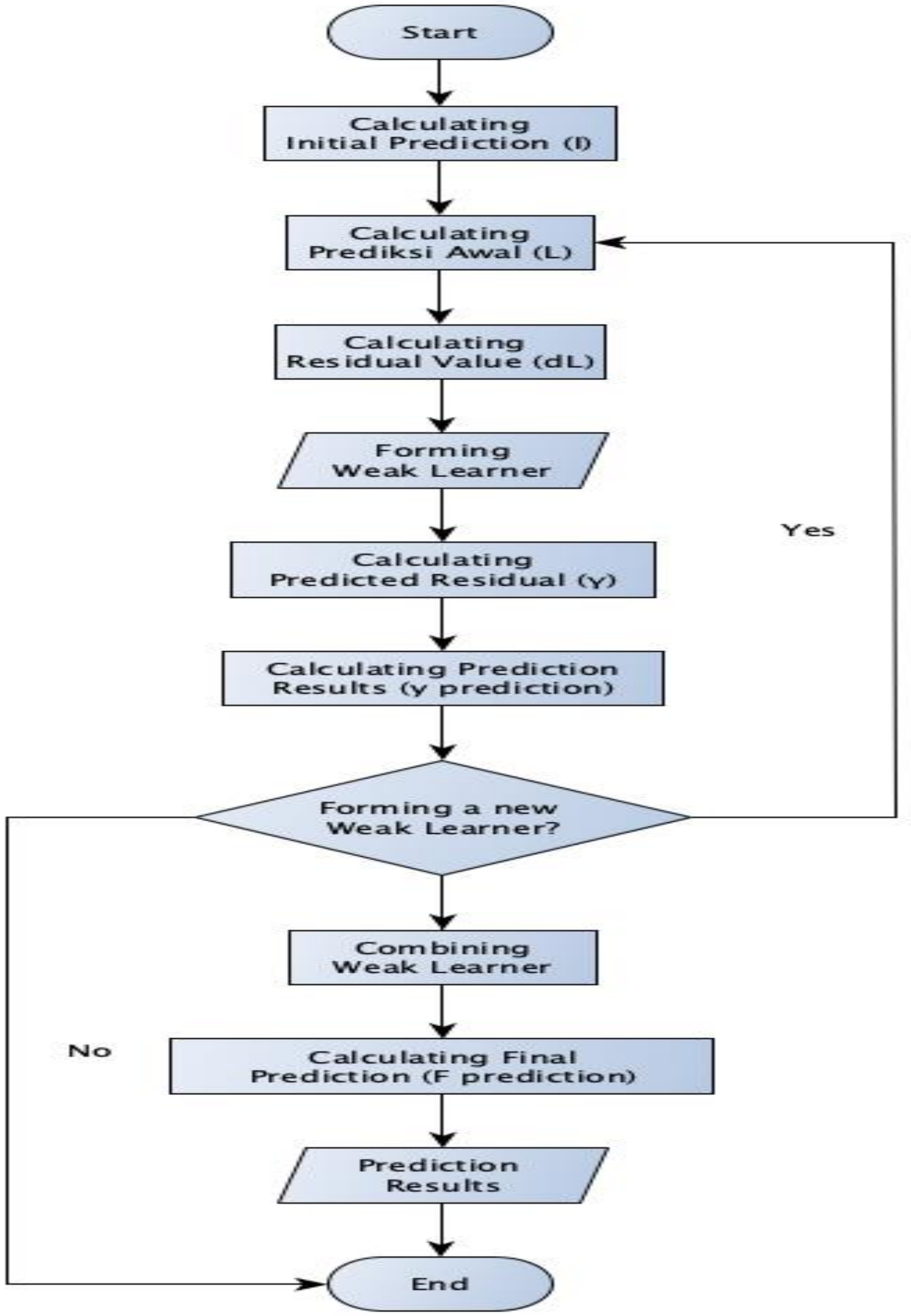

Figure 1 Gradient Boosting Flowchart

RESULTS AND DISCUSSION

The data used is 6,340 data with the attributes of Soil pH, Soil Moisture, Air Temperature and Air Humidity. The data used contains sample data measuring soil quality from farmers taken in two fields divided into three points in each plot on peanut plants in Buluh Village, Socah, Bangkalan for seven days. The following table is information regarding the data used for research in Table 3.

Table 3. Dataset

Day	Point	Soil pH	Soil Moisture	Air Temperature	Air Humidity	Label
1	1	4,74	48%	37	67%	No
…	…	…	…	…	…	…
1	2	4,44	41%	43	48%	No
…	…	…	…	…	…	…
1	3	4,37	39%	47	36%	No
…	…	…	…	…	…	…
1	4	4,25	60%	41	48%	No
…	…	…	…	…	…	…
1	5	4,06	56%	41	48%	No
…	…	…	…	…	…	…
1	6	3,84	54%	36	64%	No
…	…	…	….	….	…	…
2	1	4,84	51%	35	45%	No
…	…	…	…	….	…	…
2	6	6,2	9%	33	47%	Yes
…	…	…	…	…	…	…
7	1	4,32	65%	30	48%	Yes
…	…	…	…	…	…	…
7	6	4,32	65%	27	44%	Yes
…	…	…	…	…	…	…

Based on Table 3 above, there are 4,009 data on soil quality labeled as suitable (Yes) for peanuts planting with a percentage of 63.2% and 2,332 data labeled as not suitable (No) with a percentage of 36.8%.

Here is the workflow consisting of data preprocessing, hyperparameter tuning, and classification.

1. Data Preprocessing

The first step after reading data from the dataset is data preprocessing, at this stage data cleaning is carried out which is a process to eliminate missing values from the used dataset. After data cleaning, data transformation is required by changing the Label attribute from object to binary, where the Label categorized as suitable (Yes) becomes 1 and the label categorized as not suitable (No) becomes 0.

Table 4. Missing Value in Dataset

No	Variables	Missing Value
1	Day	0
2	Point	0
3	SoilpH	0
4	SoilMoisture	0
5	AirTemperature	0
6	AirHumidity	0
7	Label	0

Based on Table 4, the dataset used has undergone a data cleaning process that each attribute in the dataset has 0 missing values. The next step is the data transformation process, which illustrated in Figure 2.

```
df['Label'] = df['Label'].map({'Tidak': 0, 'Ya': 1})
df['Label'] = pd.to_numeric(df['Label'], errors='coerce')
```

```
cols = ['Label']

for col in cols:
    print(f"{col} has {df[col].unique()} values\n")
```

```
Label has [0 1] values
```

Figure 2 Data Transformation on Labels

2. Hyperparameter Tuning Analysis

The next stage is the tuning process using hyperparameters in Gradient Boosting modeling. Based on Table 1, there are three used hyperparameters for tuning, in the *learning_rate* parameter there are six range options, 0.15, 0.1, 0.05, 0.01, 0.005, 0.001, in *n_estimators* there are six range options, 125, 150, 175, 200, 225, 250, and in *max_depth* there are five range options, 1, 3, 5, 7, 9. After performing hyperparameter tuning with Grid Search, a total of 180 combinations were evaluated. The graph below presents the accuracy results obtained from tuning the Gradient Boosting Classifier using various hyperparameter settings. The classification of soil quality is divided into six categories, each based on a different *learning_rate* value.

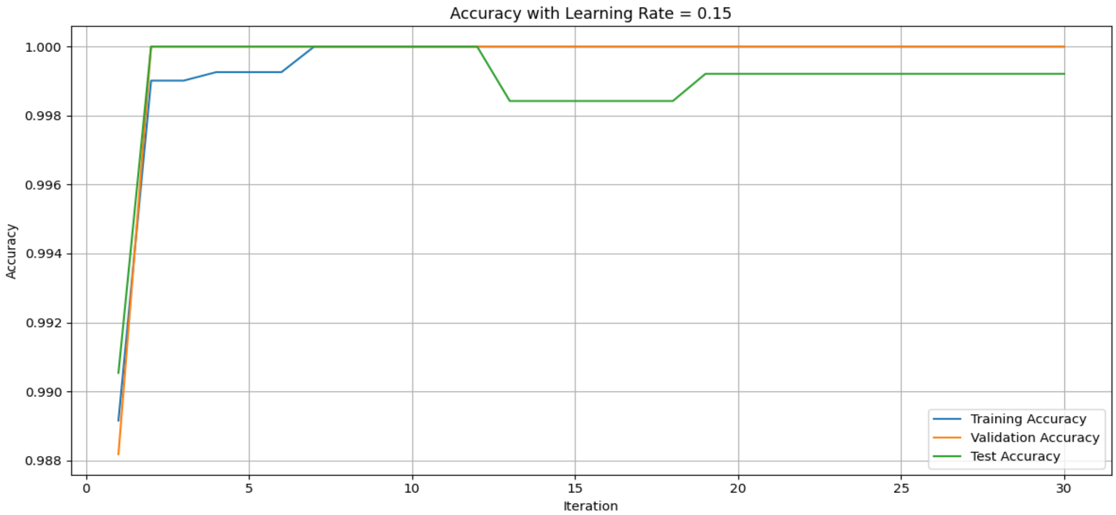

Figure 3 Accuracy Graph with *learning_rate* 0.15

Figure 3 shows the accuracy performance of the Gradient Boosting Classifier with a learning rate of 0.15. Training, validation, and test accuracy increase rapidly and remain high, nearing 1.0. A slight fluctuation in validation accuracy around iteration 15 suggests minor adjustments in the model. Overall, the model demonstrates strong generalization and effective classification of soil quality.

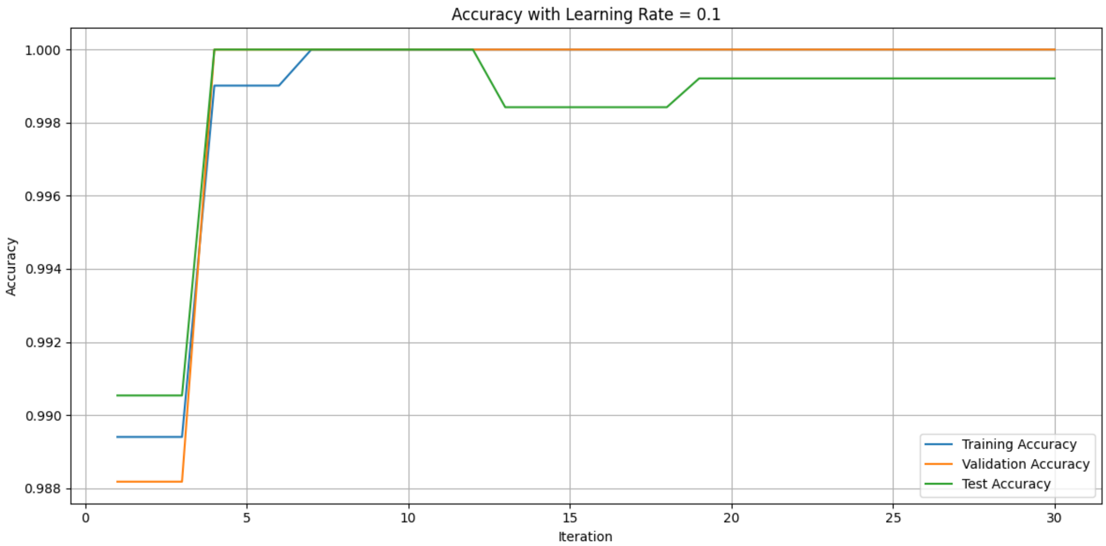

Figure 4 Accuracy Graph with *learning_rate* 0.1

Figure 4 displays the accuracy performance of the Gradient Boosting Classifier with a learning rate of 0.1. Training, validation, and test accuracy rapidly increase and stabilize near 1.0, indicating strong model performance. A slight drop in validation accuracy around iteration 15 suggests minor fluctuations, but overall, the model maintains high accuracy and effective soil quality classification.

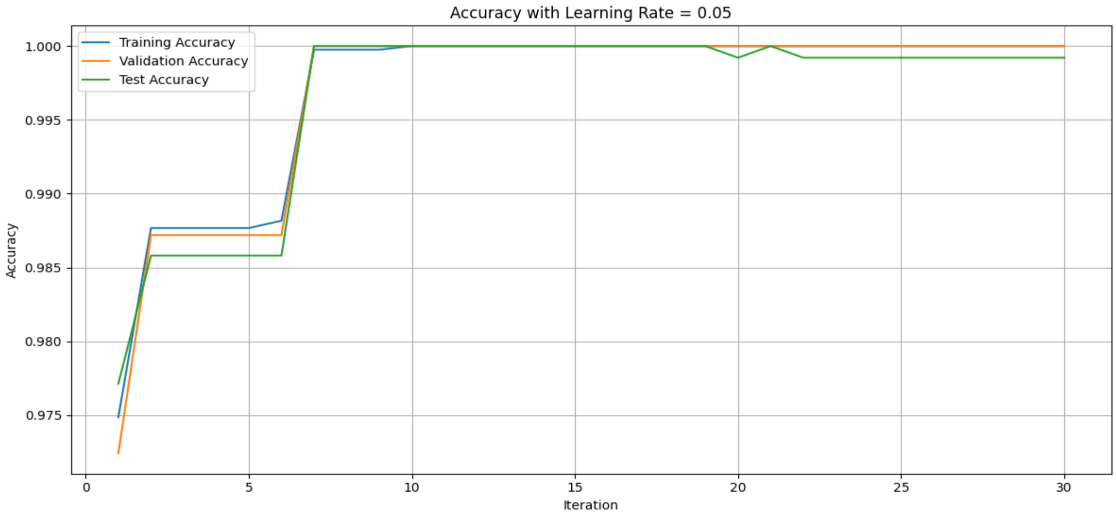

Figure 5 Accuracy Graph with *learning_rate* 0.05

Figure 5 shows the accuracy performance of the Gradient Boosting Classifier with a learning rate of 0.05. Accuracy for training, validation, and test sets increases steadily and stabilizes close to 1.0. Minor fluctuations appear around iteration 20, but overall, the model maintains high accuracy, indicating effective soil quality classification.

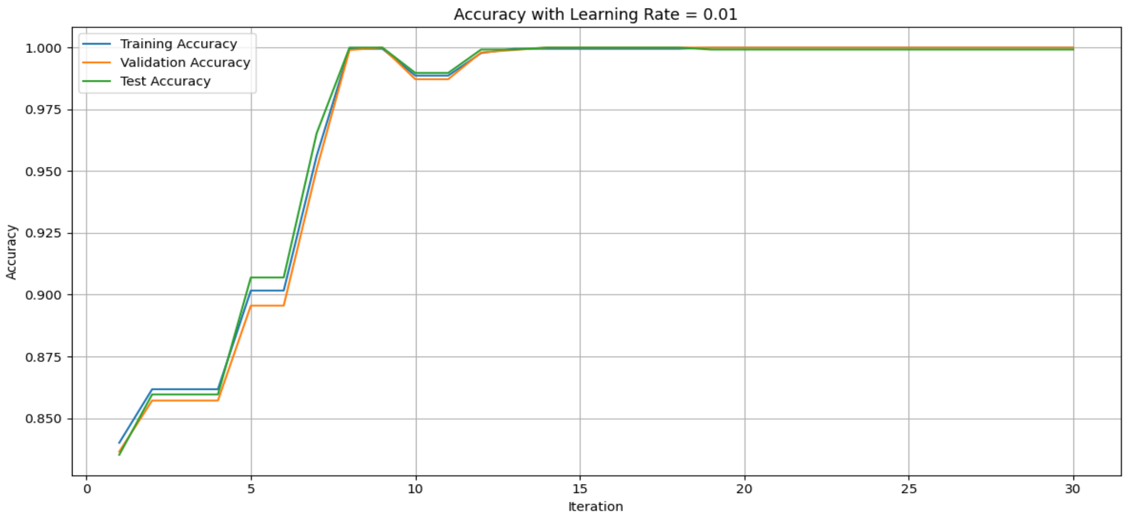

Figure 6 Accuracy Graph with *learning_rate* 0.01

Figure 6 illustrates the accuracy performance of the Gradient Boosting Classifier with a learning rate of 0.01. Initially, accuracy increases gradually before sharply improving around iteration 7, stabilizing near 1.0. Minor fluctuations occur between iterations 10 and 15, but the model ultimately maintains high accuracy, demonstrating effective soil quality classification.

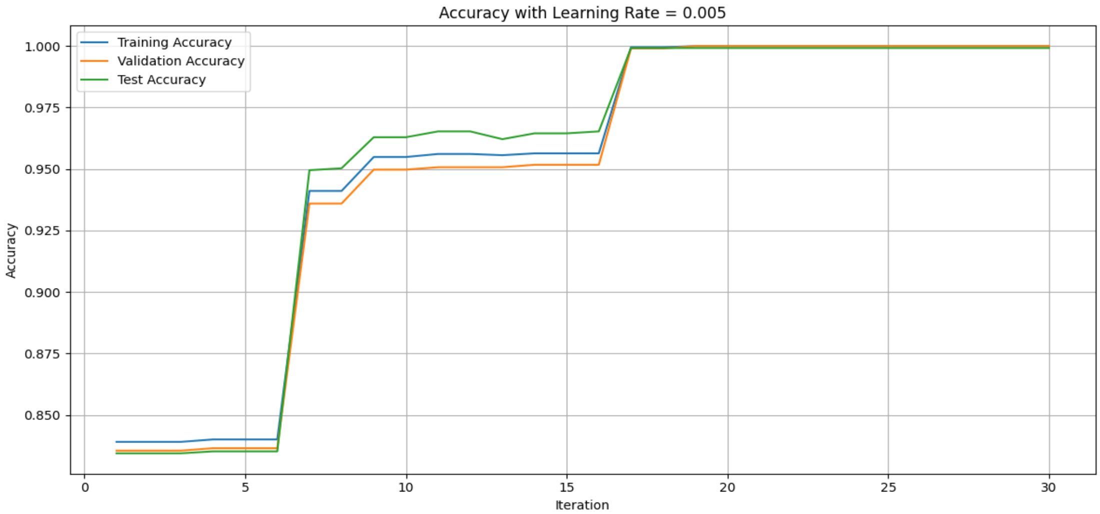

Figure 7 Accuracy Graph with *learning_rate* 0.005

Figure 7 represents the accuracy trend of the Gradient Boosting Classifier with a learning rate of 0.005. The accuracy remains low in the initial iterations but then rapidly increases around iteration 7. A gradual improvement continues, reaching near 1.0 after iteration 18, where it stabilizes. The model effectively classifies soil quality with high accuracy.

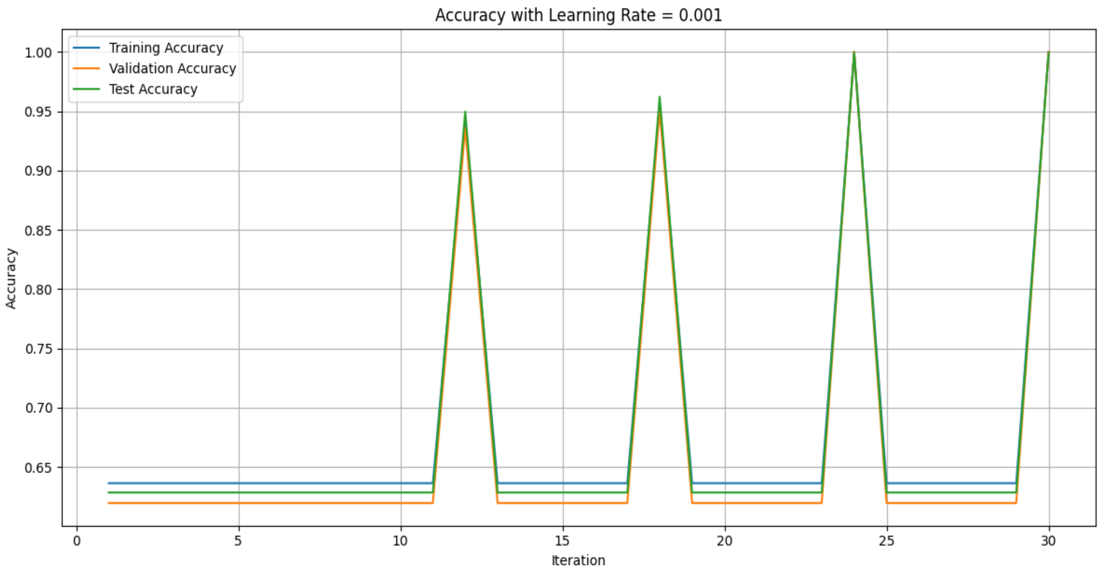

Figure 8 Accuracy Graph with learning_rate 0.001

Figure 8 illustrates the accuracy trend of the Gradient Boosting Classifier with a learning rate of 0.001. The accuracy remains consistently low at around 0.65 for most iterations, with periodic spikes reaching nearly 1.0 at certain intervals. These fluctuations indicate instability in model performance, suggesting that the chosen learning rate may be too low for effective convergence.

Table 5 Grid Search Tuning Results

Parameter	Explanation	GridSearch Values	Best Parameter
learning_rate	Size reduction is used to prevent overfitting.	0,15; 0,1; 0,05; 0,01; 0,005; 0,001	0,15
n_estimators	Number of trees to be used	125, 150, 175, 200, 225, 250	150
max_depth	Maximum depth of the tree to be formed	1, 3, 5, 7, 9	1

Based on Table 5, the tuning results in the Gradient Boosting classification produce an *n_estimators* value of 150, then each tree formed will have a *max_depth* of 1 which is the branching or depth of the tree and the *learning_rate* used is 0.15 which can function as a learning rate that affects the Gradient Boosting algorithm in the classification process in the form of a tree.

3. Classification Results

The Gradient Boosting method used for classification produces an accuracy value of 100% using the used hyperparameters in the tuning process with Grid Search consists parameters of *learning_rate* = 0.15; *max_depth* = 1 and *n_estimators* = 150, the used model performs accurate classification of all 1,268 samples data according to the actual class.

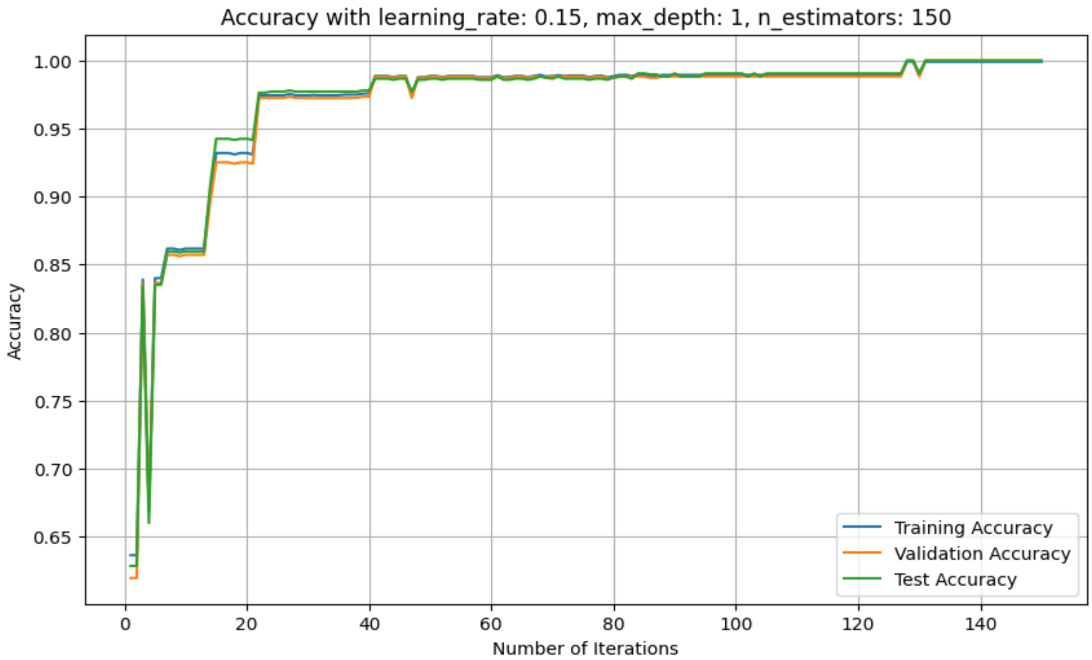

Figure 9 Accuracy with Tuning Hyperparameters

After gathering the model from Gradient Boosting with tuning using Grid Search on hyperparameters, then model evaluation is carried out. Steps taken to evaluate the prediction results of the model such as the size of the Accuracy, Precision, Recall/Sensitivity, and Specificity values can be done using the Confusion Matrix.

Table 6 Confusion Matrix

Current	**Prediction**	
	Negative	Positive
Negative	471	0
Positif	0	797

In Table 6, the used data for the data testing process is 1,268 data with a true positive value of 797 data and a true negative of 471 data. The data generated by the confusion matrix is the result of splitting data testing and data training then comparing the model between the predictions of the used model and the actual labeled data in the dataset. To calculate the accuracy value in the confusion matrix using the following equation.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100\%$$

$$= \frac{797 + 471}{797 + 471 + 1 + 0} \times 100\%$$

$$= \frac{1268}{1268} \times 100\%$$

$$= 100\%$$

Based on accuracy calculation, it can be seen that the level of perfection between the predicted value and the actual value is 100% which means that the Gradient Boosting method classifies between the predicted class and the actual class perfectly where the 1,268 samples can be classified correctly. Furthermore, to calculate the precision value using the following equation.

$$Precision = \frac{TP}{(TP+FP)} \times 100\%$$

$$Precision = \frac{797}{797 + 0} \times 100\%$$

$$Precision = \frac{797}{797} \times 100\%$$

$$Precision = 100\%$$

From the precision calculation, it can be seen that the precision value for classification has accurate prediction results with a value of 100%. Furthermore, to calculate the recall value using the following equation.

$$Sensitivity = \frac{TP}{(TP+FN)} \times 100\%$$

$$Sensitivity = \frac{797}{797 + 0} \times 100\%$$

$$Sensitivity = \frac{797}{797} \times 100\%$$

$$Sensitivity = 100\%$$

From the sensitivity calculation, a value of 100% is obtained, which means that the proportion of positive classes correctly classified by the system has been well developed. Furthermore, to calculate the specificity value using the following equation.

$$Specificity = \frac{TN}{(TN+FP)} \times 100\%$$

$$Specificity = \frac{471}{471+0} \times 100\%$$

$$Specificity = \frac{471}{471} \times 100\%$$

$$Specificity = 100\%$$

From the specificity calculation, a value of 100% is obtained, which means that the proportion of negative classes correctly classified by the system is perfect in the classification using the Gradient Boosting method.

CONCLUSION

Based on research that has been conducted using soil quality data on peanut cultivation in Buluh Village, Socah, Bangkalan using the Gradient Boosting classification method, several conclusions can be drawn in the following text:

1. The tuning process using Grid Search has been done using the available library. The tuning results using Grid Search produce the best parameter values with *learning_rate* = 0.15; *max_depth* = 1 and *n_estimators* = 150.
2. The data used were 6,340 data, divided into testing data and training data. The used testing data for model evaluation were 1,268 data which produced 797 true positive data and 471 true negative data with an accuracy result of 100% with hyperparameters.
3. Based on the tuning process that has been processed, it can be concluded that the smaller the *learning_rate, max_depth*, and *n_estimators* used, the smaller the accuracy results that will be produced by the used model.

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