# Prediction of land suitability for food crop types using classification algorithms

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**Article Info**

***Article history:***

Received Dec 6, 2024
Revised Aug 5, 2025
Accepted Sep 10, 2025

***Keywords:***

AdaBoost
Classification algorithm
Prediction
Random forest
Type of food crops

**ABSTRACT**

Decision-making in the selection of crop types is often conducted using conventional approaches. It is relying on limited experience and knowledge without considering the latest data or information. This approach has the loss of opportunities to use crop types. The crop types are more suited to environmental conditions and market demand, and it inhibits the application of innovation in agriculture. Therefore, the use of information technology becomes crucial to enhance accuracy in determining land suitability and crop selection. This study recommends the random forest (RF) algorithms and AdaBoost due to their excellent performance across all metrics (under the curve (AUC), classification accuracy (CA), F1, precision, recall) on various dataset sizes with scores above 0.9, so it is the solution to predict land suitability for specific crop types. Furthermore, it enables farmers to maximize land potential and achieve optimal yields.



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## 1. INTRODUCTION

Indonesia is a large population country. In continuing an experience development, this course has an impact on food needs which also experience an increase. Selecting the right type of crop for land conditions will increase agricultural productivity and ensure food security [1]. In addition, by increasing productivity, it will increase income, help reduce poverty, and improve the quality of life in rural areas. Efficient and sustainable land use will create a good balance between food production, environmental conservation, and other economic activities [2], [3].

Decision-making regarding crop types in many cases is done conventionally. It is relying on limited knowledge and experience without considering broader data or more relevant to up-to-date information [4]. Conventional approaches may not consider alternative crop types that are more suited to current environmental conditions and market demand. These missed opportunities to utilize more profitable crop types can significantly hinder agricultural efficiency. Conventional approaches can block the adoption of innovative practices, like the use of disease-resistant or climate-resilient crop varieties, and advanced agricultural technologies. Therefore, leveraging information technology becomes crucial in facilitating optimal decision-making regarding land suitability and crop selection, ensuring a more efficient and profitable agricultural process.

Agricultural land in South Ogan Komering Ulu Regency includes 1,680 hectares of wetland (rice fields) and 11,968 hectares of dry land (dry fields), accounting for around 3.31% of the total district area. The regency spans approximately 5,849.89 km² (549,394 hectares) with a topography ranging from 45 to 3,221 meters above sea level, featuring hilly and mountainous regions. The highest point is Mount Pesagi in Warkuk Ranau Selatan District, standing at 3,221 meters. The region experiences temperatures between 22 °C to 31 °C and annual rainfall of 2,038 mm. From these conditions, the land is predominantly used for plantation and horticulture, cultivating crops like oil palm, coconut, rubber, coffee, cocoa, pepper, cloves, and sugar palm. However, cultivation of food crops such as rice, corn, and cassava remains minimal. Therefore, the existing agricultural land has not been fully optimized for its potential.

Nowadays, predictive modeling technology is becoming increasingly important in supporting smarter and more precise decision making. Ganesan *et al.* [5] have conducted research to make predictions, which predict land suitability for plant types using supervised learning algorithms, namely decision trees (DT), random forests (RF), support vector machines (SVM), and K-nearest neighbors (KNN). Furthermore, the study was conducted by Istiawan [6] which is predicting critical land in crop cultivation areas using the C.45, ID3, RF, KNN, and Naïve Bayes (NB) algorithms. Critical land is land that is not suitable or does not support optimal plant growth. This is caused by several factors including soil degradation, erosion, and other environmental factors. Understanding critical land predictions is essential for sustainable land management. Next, predicting plant suitability using the decision tree-based ensemble learning method. This method is applied to help farmers make better decisions about the most suitable plants to be planted on a land and maximize productivity [7].

The researcher also conducts the similar research utilizing classification algorithms to predict land suitability for various plant types. The algorithms used include RF, KNN, NB, SVM, AdaBoost, and neural network (NN). Based on the performance metrics of each algorithm, the most effective one for making predictions will be recommended. This approach enables land managers to make more informed and precise decisions regarding crop selection, ultimately enhancing productivity, optimizing resource usage, and ensuring the sustainability of land management practices.

## 2. METHOD

This study is conducted in several stages in accordance with cross-industry standard process for data mining (CRISP-DM), namely from business understanding; data understanding; data preparation; modeling; evaluation; and deployment, as in Figure 1. The purpose of this study is to predict land suitability in business understanding with types of plants, especially food crops based on land characteristic data, in this case the land condition in Buay Pemaca District, South Ogan Komering Ulu Regency. Data understanding is obtained from the Department of Agriculture, Food Crops and Horticulture of South Ogan Komering Ulu Regency in the form of soil characteristic data from several villages in Buay Pemaca District consisting of soil pH, soil drainage, soil texture, moisture, and nutrients with target labels, namely corn, rice and cassava, with the file name dataset_1.

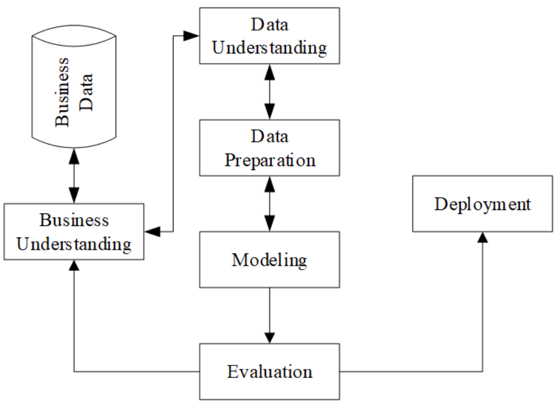


Figure 1. The stages of CRISP-DM

Data preparation involves refining the dataset to ensure its quality and usability for analysis. Some data points are combined to be separated to attribute correct values to specific features. The feature representing village names is excluded from the prediction process since it does not influence land suitability and crop type predictions. The dataset contains 188 records, classifying it as small data. Additionally, the study incorporates public datasets from Kaggle to enhance the robustness and comprehensiveness of the analysis [8]. This data has 8 features, namely nitrogen, phosphorus, potassium, temperature, humidity, pH, rainfall, and labels for plant types. As for the types of plants, namely apple, banana, blackgram, chickpea, coconut, coffee, cotton, grapes, jute, kidneybeans, lentils, maize, mango, mothbeans, mungbean, muskmelon, orange, papaya, pigeonpeas, pomegranate, rice, and watermelon. The number of records from the crop-recommendation data is 2200, and we save it with the file name dataset_2.

Modeling is the predictions to be made using several classification algorithms, namely RF, KNN, NB, SVM, AdaBoost, and NN. The dataset is divided into training and test sets to build and validate the models. Evaluation is evaluated by measuring accuracy, precision, recall, F1-score, or receiver operating characteristic (ROC) curve. The final stage is deployment. It carried out by implementing the model that has been trained and evaluated in the existing environment or with larger data.

This study will use six classification algorithms, which will then be evaluated so that the algorithm with the best performance will be obtained to be recommended in predicting land suitability with plant types. Here are the details of how each algorithm works.

### 2.1. Random forest

The RF algorithm is a predictive modeling method that has proven effective in various applications, including land suitability analysis [9], [10]. This algorithm is able to handle data of various types and complexities well, and provides accurate and easily interpretable results, as well as its ability to identify non-linear relationships between variables [11], [12]. How the RF algorithm works can be seen in Figure 2.

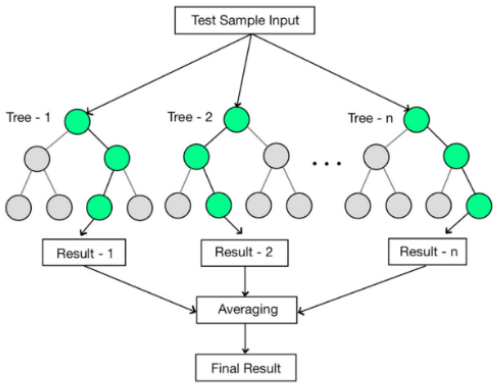


Figure 2. RF algorithm prediction [12], [13]

### 2.2. K-nearest neighbors

The KNN algorithm is a machine learning algorithm for classification and regression [14], [15]. This algorithm does not have an explicit training process so it is included in the lazy learning category. KNN only stores training data and makes predictions when there is new data requested to be classified. This is because KNN has several advantages including being easy to apply to solve various problems. Tolerant to datasets that have noise. Able to process quickly even with large data conditions [15]. So, it is widely used in various fields including KNN to overcome the problem of high data imbalance. It is done with modifications with several other approaches, such as quad division prototype selection [16]. KNN is used to estimate forest stand variables using airborne laser data [17].

### 2.3. Naïve Bayes

The NB algorithm is a statistical classification method based on Bayes' theorem with the assumption of independence between features [18], [19]. NB is used to predict the class of data based on probability; by calculating the probability that a particular data belongs to a certain class. The NB algorithm is widely used because it is simple, fast, easy to implement, and effective on large datasets [20]. The NB algorithm is used to predict COVID-19 infection among individuals who have close contact with confirmed patients [21]. Integrating association rules into NB algorithm for coronary heart disease diagnosis [22].

### 2.4. Support vector machines

SVM is a sophisticated machine learning algorithm that has proven to be very effective in classifying data by finding the optimal hyperplane in high-dimensional space [23]. SVM as a classification algorithm is used to separate data into two or more classes by finding the optimal hyperplane. SVM is well known for its ability to handle non-linear data and to provide high accuracy in many classification applications. In addition, SVM has proven to be a powerful and effective technique for handling various classification problems in the real world [24]. Implementation of SVM includes predicting areas prone to landslides [25], to model Marshall Stability on polypropylene fiber reinforced asphalt concrete [26], and many more.

### 2.5. AdaBoost

AdaBoost is one of the most popular ensemble methods, which uses a weighting process to improve the performance of weak classifiers. The AdaBoost algorithm is easy to implement and is capable of significantly improving classification accuracy. In addition, this method can be applied with various types of classifier [27]. The main idea of AdaBoost is to train a set of weak classifiers, then combine them through certain rules, such as linear combination, to form a stronger classifier. In this way, weak classifiers are transformed into more accurate strong classifiers [28]. AdaBoost has proven to be very effective in various studies, such as a network-based intrusion detection system that uses a combination of the artificial bee colony (ABC) algorithm and AdaBoost to detect anomalies in a network [29]. UAV data link anti-interference using the sequential Latin hypercube sampling (SLHS)-support vector machine (SVM)-AdaBoost algorithm aims to improve communication reliability in unmanned aerial vehicles. This approach consists of two main components: classification prediction and route planning [30].

### 2.6. Neural network

Artificial neural networks (ANN) for classification are machine learning models inspired by the way the human brain works [31]. This model is used to classify data into different categories. NN have been applied in various fields, such as fiber optic-based sensing systems that use NN to classify vehicles [32]. NN to predict stroke risk in individuals based on health data and relevant risk factors [33], and others.

## 3. RESULTS AND DISCUSSION

This study predicts land suitability for various food crops using several classification algorithms, including RF, KNN, NB, SVM, AdaBoost, and NN. The performance of these algorithms is evaluated using a confusion matrix. Based on this evaluation, the algorithm with the best performance will be recommended for practical use in land suitability prediction. The developed model and its evaluation results are depicted in Figure 3.

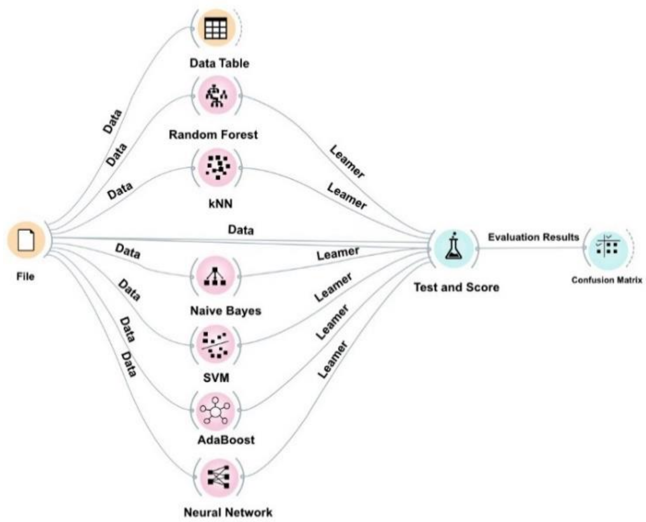


Figure 3. The Classification model for predicting land suitability for food crop types

This study uses two datasets to evaluate the performance of the classification model, namely dataset_1 and dataset_2. Where each dataset is then processed with the RF, KNN, NB, SVM, AdaBoost, and NN algorithms. Furthermore, it is evaluated using a confusion matrix for accuracy, precision, recall, F1-score. The experimental results of the classification model can be seen in Tables 1 and 2.

Table 1. The comparison of classification algorithm performance in predicting land suitability with food crop types using dataset_1

| Algorithm | Under the curve (AUC) | Classification accuracy (CA) | F1 | Precision | Recall |
|---|---|---|---|---|---|
| SVM | 0.994 | 0.968 | 0.968 | 0.971 | 0.968 |
| RF | **1.000** | **0.995** | **0.995** | **0.995** | **0.995** |
| NN | 0.995 | 0.995 | 0.995 | 0.995 | 0.995 |
| NB | 0.967 | 0.889 | 0.886 | 0.908 | 0.889 |
| KNN | 0.996 | 0.995 | 0.995 | 0.995 | 0.995 |
| AdaBoost | **1.000** | **1.000** | **1.000** | **1.000** | **1.000** |

Table 2. The comparison of classification algorithm performance in predicting land suitability with food crop types using dataset_2

| Algorithm | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| SVM | 0.996 | 0.882 | 0.882 | 0.888 | 0.882 |
| RF | **0.999** | **0.974** | **0.974** | **0.975** | **0.974** |
| NN | 0.998 | 0.932 | 0.932 | 0.933 | 0.932 |
| NB | 0.997 | 0.903 | 0.902 | 0.905 | 0.903 |
| KNN | 0.940 | 0.766 | 0.763 | 0.776 | 0.766 |
| AdaBoost | **0.980** | **0.962** | **0.962** | **0.963** | **0.962** |

The evaluation results in Table 1 show that the AdaBoost algorithm has very good performance, this is indicated by the results of the matrix evaluation of AUC, CA, F1, precision and recall with a value of 1. This occurs because the size of the dataset_1 data is small, besides the data is clean, structured and simple. The next best is the RF algorithm which is indicated by an AUC value of 1, while for CA, F1, precision and recall are 0.995. Followed by the NN, KNN, SVM, and NB algorithms.

The evaluation results in Table 2 show that the algorithm with the best performance is RF, this is indicated by the most superior values in AUC, CA, F1, precision and recall, respectively with values of 0.999; 0.974; 0.974; 0.975; and 0.974. Followed by the second best is the AdaBoost algorithm with values of 0.980; 0.962; 0.962; 0.963; and 0.962. Followed by the NN, NB, SVM, and KNN algorithms.

## 4. CONCLUSION

Decision-making in crop selection frequently relies on conventional methods that depend on limited experience and outdated information. This traditional approach overlooks the potential of alternative crops better suited to specific environmental conditions and market demands. It also hampers the adoption of innovative solutions like disease-resistant crop varieties and advanced agricultural technologies. Thus, integrating information technology is essential to enhance decision-making processes regarding land suitability and optimal crop selection, ensuring a more efficient, adaptive, and sustainable agricultural practice. The evaluation results indicate that the RF and AdaBoost algorithms demonstrate superior performance across all metrics (AUC, CA, F1, precision, recall) for both small and large datasets, consistently achieving values above 0.9. This performance surpasses that of other algorithms such as NN, NB, SVM, and KNN. Consequently, this study recommends the use of RF and AdaBoost algorithms as effective tools for predicting land suitability for food crops. These algorithms enable farmers to optimize land use, thereby achieving maximum yield and efficiency.

## FUNDING INFORMATION

This study was funded by a Doctoral Research Grant for 2024 in SK.0369/DMJ/REK/LPPM/VII-2024, organized by Institut Informatika dan Bisnis Darmajaya.

## AUTHOR CONTRIBUTIONS STATEMENT

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| Suci Mutiara | | | ✓ | | | ✓ | | | ✓ | | | | ✓ | |

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| C : **C**onceptualization | I : **I**nvestigation | Vi : **Vi**sualization |
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| Va : **Va**lidation | O : Writing - **O**riginal Draft | Fu : **Fu**nding acquisition |
| Fo : **Fo**rmal analysis | E : Writing - Review & **E**diting | |

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

There are 2 types of research data, namely data taken from https://www.kaggle.com/ and data obtained from the Department of Agriculture, Food Crops and Horticulture of South Ogan Komering Ulu Regency.

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