Implementation Of Naïve Bayes Method In Food Crops Planting Recommendation

Tedy Setiadi, Fiftin Noviyanto, Hendika Hardianto, Ali Tarmuji, Abdul Fadlil, Merlinda Wibowo

Abstract: In recent years the erratic weather changes have led to various polemics. Indonesia as an agricultural country with a large part of the population earning a living in agriculture feels real impacts such as crop failure. The use of cropping patterns that have been carried out from generation to generation without regard to climate change and the environment is the cause. Technology changes in agriculture needs by utilizing government-owned data to help farmers by providing recommendations for food crops. This study aims to use a data classification technique with the Naïve Bayes algorithm in obtaining the results of the recommendation of food plant types. Data obtained from the Provincial Office of DI. Yogyakarta. The parameters considered are the weather, yields, and selling prices of the four districts in the province. Data selection and data cleaning are needed to retrieve attributes that affect the results of recommendations. To find out the performance of Naïve Bayes to the dataset, use WEKA. The cross-validation method is used to validate data. The results showed an accuracy of 85.71%. Naïve Bayes is feasible to be used for a dataset of recommended crop species, supported by the results of the sensitivity 0.857 and a specificity of 0.862 as validation. Naïve Bayes consistency is consistent with the Kappa Statistics value of 0.8084. Besides, the method error when classifying and the time has taken also calculated.

Index Terms: Agriculture, Planting Recommendation, Naïve Bayes, Food Plant

1 INTRODUCTION

Most of Indonesia's population earns a living as a farmer. Therefore Indonesia is predicated as an agrarian country. Farmers, especially in the Special Province of Yogyakarta, still use traditional planting patterns, to determine the types of plants to be planted. This method has been carried out for generations. But climate conditions have changed [1]. So that the method of farmers in determining the crop is less than the maximum because the climate affects the productivity of agricultural land [2][3], especially for food crops [4]. Therefore, it is necessary to improve the productivity of farmers by minimizing errors in choosing the type of plants to be planted. BMKG data contains climate data such as rainfall, temperature, humidity, angina velocity in certain areas. The public can access BMKG data that is updated regularly. Daily weather reports are also available in certain areas. After going through a long process to be able to publish agricultural data, including yields, harvested area, and productivity, the Agriculture Office presents data in one growing season to harvest, which is four months. The Food Security and Counseling Agency (BKPP) updates the data every week. Getting high yields is hope for every farmer. Paying attention to the factors that influence yields can help farmers in making decisions. Utilization of Information and Communication Technology (ICT) has been successfully implemented in various climatic conditions [5]. Especially the use of artificial intelligence provides a more effective approach [6]. Various studies have been conducted to predict food crops with various methods that have been tested in various ways. Modern agricultural techniques that have used data on soil characteristics, crop yields and weather and other related data in suggesting farmers determine crop types according to parameters in the field [7]. The use of Naïve Bayes is very efficient in calculations so that it can test various plants. This model focuses on all types of agriculture, and small farmers can benefit [8]. An ensemble model with decision-making techniques using Random Tree, CHAID, K-Nearest Neighbor and Naïve Bayes as learners to recommend food crops based on certain parameters inputted through the website results in high accuracy and effectiveness . [7]. Determining the Soft Computing planting calendar produces better predictions if supported by the Moving Average algorithm by obtaining an accuracy of 91.67% for food crops, corn, and potatoes [9]. The Neural Network neural network method has been used in predicting to determine the start of the season for rice, maize, and potato. The accuracy obtained is> 75%. There is an accuracy difference of around 2.54% due to differences in data usage, between data from the Department of Agriculture and BMKG [10]. Prediction and detection of rainfall anomalies using the Evolving Neural Network obtained 84.6% accuracy in all data scenarios. The addition of hidden layers to the Neural Network architecture increases computing time by 50% [11]. Helping farmers to determine cropping patterns in accordance with weather conditions using the Decision Tree [12]. The study uses weather and crop yield data services to determine what types of plants are suitable for planting in a certain period. It is necessary to add other factors in recommending plant types not only based on weather conditions, in this study adding crop yields and selling prices to consider the types of food plants to be planted.

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2 RESEARCH METHOD

In this research, we will examine the performance of the Naïve Bayes method to predict food crop recommendations. The research model was developed from previous research models. The stages of the methodology used are Data

Collection, Data Pre-processing, Naive Bayes Method Testing, Evaluation and Validation, and Validation, and Results and Discussion are illustrated in Figure 1.

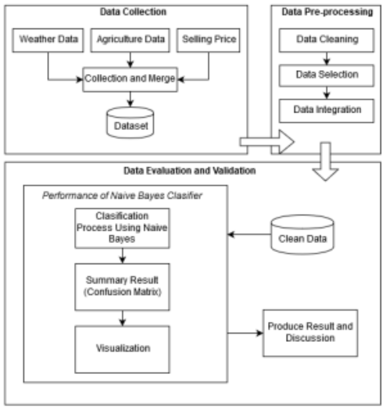

***Fig. 1**. Research Stages*

The stages are started from data collection, data obtained from BMKG, Agriculture office, and BKPP. The data obtained is then combined into a dataset. In the second stage, not all data in the dataset is used for this study, therefore there is a need for a pre-processing stage. In the next stage, apply Naïve Bayes to clean data, to find out its performance. The last stage is the discussion of results and discussion.

2.1 Study Area

The Special Region of Yogyakarta (DIY) is located in the southern part of the island of Java and is bordered by the Provinces of Central Java and the Indian Ocean. The Special Region which has an area of 3,185.80 km2 consists of one municipality, and four districts namely, the City of Yogyakarta, Gunungkidul, Bantul, Kulon Progo, and Sleman

2.2 Data Collection

Data obtained privately from several offices in DIY. Weather data were obtained from the Meteorology Climatology and Geophysics Agency (BMKG) of the DIY Province.

BMKG

ID WMO : 96855
Nama Stasi : Stasiun Geofisika Yogyakarta
Lintang : -7.82000
Bujur : 110.30000
Elevasi : 153

Bulan	Tavg	RH_avg	AP	Ff_avg	DoS	RR	RD
Januari	26.0	88.0	1012.5	0.9	37	455	27
Februari	26.1	87.6	1013.2	1.0	48	430	24
Maret	26.3	87.0	1013.3	0.9	57	436	21
April	26.5	87.6	1013.8	0.8	59	372	20
Mei	26.4	83.4	1014.1	0.8	75	184	7
Juni	26.3	84.1	1014.5	0.7	66	62	5
Juli	25.1	83.8	1015.7	0.8	55	28	4
Agustus	26.3	80.7	1015.5	1.0	70	1	1
September	25.8	81.4	1015.5	1.1	67	191	6
Oktober	26.9	83.7	1014.3	1.0	57	274	14
November	25.8	89.6	1011.8	0.8	26	928	25
Desember	26.3	85.9	1012.5	1.0	52	372	22

Ket :
Tavg : Temperatur rata-rata (°C)
RH_avg : Kelembapan rata-rata (%)
AP : : Tekanan Udara (mb)
Ff_avg : Kecepatan Angin rata-rata (knot)
DoS : Lama Penyinaran Matahari (%)
RR : Curah Hujan (mm)
RD : Jumlah Hari Hujan

***Fig. 2**. BMKG Weather Data Samples*

Figure 2 is a sample weather data in 2017. Weather data are obtained monthly from Yogyakarta Geophysics Station. Various weather parameters recorded by BMKG such as air temperature, humidity, air pressure, wind speed, duration of sun exposure, rainfall and number of days of rain. The next data is to harvest data obtained from the Yogyakarta Provincial Agriculture Office.

ANGKA TETAP TAHUN 2017 PRODUKSI PADI DAN PALAWIJA PROVINSI D.I YOGYAKARTA

JAGUNG

No	Kabupaten/Kota	Januari - April (Realisasi)			Mei - Agustus (Realisasi)			Sept - Des (Realisasi)			Januari - Desember		
		LP	Ku/ha	Produksi	LP	Ku/ha	Produksi	LP	Ku/ha	Produksi	LP	Ku/ha	Produksi
1	Kulonprogo	1,268.0	64.28	8,151	267.1	55.99	1,495	2,652	73.60	19,522	4,187.5	69.65	29,168
2	Bantul	212.8	58.63	1,248	256.7	58.70	1,507	2,813	93.33	26,255	3,282.6	88.38	29,010
3	Gunungkidul	44,830.9	41.06	184,076	3,671.9	54.16	19,887	424	60.41	2,563	48,927.1	42.21	206,526
4	Sleman	333.9	49.20	1,643	98.6	66.12	652	5,691	78.66	44,765	6,123.4	76.85	47,060
	JUMLAH KAB (tanpa KOTA)	46,645.6	41.83	195,118	4,294.3	54.82	23,541	11,581	80.40	93,105	62,520.6	49.87	311,764
5	Yogyakarta												
	JUMLAH KAB/KOTA	46,645.6	41.83	195,118	4,294.3	54.82	23,541	11,581	80.40	93,105	62,520.6	49.87	311,764

***Fig. 3**. Samples of Production Data, Productivity, and Harvest Area*

Fig 3 is an example of rice and secondary crop production data obtained from the Department of Agriculture in the period of 2013 to 2017. The data obtained in the form of data on harvest area per hectare, productivity, namely harvest per hectare in quintals, and yields in tons. The agriculture office presents data in quarterly terms. Data from each district and city is recorded by the agriculture department. While the selling price is obtained from the Food Security and Counseling Agency (BKPP).

TABLE 1

SAMPLE SALES PRICE DATA

		BANTUL				
Commodity	*Unit*	*Week 1*	*Week 2*	*Week 3*	*Week 4*	*Average*
Farmer Level GKP	*Rp/Kg*	*4,425*	*4,550*	*4,600*	*4,625*	*4,550*
Dry Corn Corn Farmer Level	*Rp/Kg*	*3,400*	*3,425*	*3,450*	*3,475*	*3,438*
Dried Soybean Seed Farmer Level	*Rp/Kg*	*6,725*	*6,900*	*6,950*	*6,950*	*6,881*
Onion Farmer Level	*Rp/Kg*	*18,125*	*17,625*	*15,500*	*16,250*	*16,875*
Curly Red Chili Farmer Level	*Rp/Kg*	*21,000*	*19,250*	*28,500*	*30,875*	*24,906*
Milling Level GKP	*Rp/Kg*	*4,575*	*4,696*	*4,783*	*4,783*	*4,709*
MPD Grinding Level	*Rp/Kg*	*5,617*	*5,725*	*5,750*	*5,725*	*5,704*
Medium Rice Milling Level	*Rp/Kg*	*9,475*	*9,792*	*9,800*	*9,925*	*9,748*
Milling Level Premium Rice	*Rp/Kg*	*10,933*	*11,392*	*11,767*	*11,767*	*11,465*

Table 1 is an example of selling price data at the producer level obtained from BKPP DIY. Various food crop commodities and other crops are presented weekly by week. The selling price is presented in units of rupiah per kilogram. The data obtained ranges from 2015 to 2017.

2.3 Data Pre-processing

In this research, not all data are used. From various weather data, it only uses some weather elements that have an influence on the growth of food crops, namely, temperature (° C), humidity (%), light intensity (W / m2), and rainfall (mm3) [13]. For data from the Department of Agriculture using data on the results of food crop production. and using sales price data obtained from the BKPP.

TABLE 2

SAMPLE DATA SET RESEARCH

Bulan	Tavg	RH_avg	DoS	RR	Produksi	Harga	Keuntungan	Tanaman
Januari	26.0	88.0	37	455	246	8911	3506	Kacang Tanah
Februari	26.1	87.6	48	430	13,991	2237	1690	Ubi Kayu
Maret	26.3	87.0	57	436	68,126	3671	1895	Padi
April	26.5	87.6	59	372	1,507	4698	3250	Jagung
Mei	26.4	83.4	75	184	236,963	3675	1220	Padi
Juni	26.3	84.1	66	62	179,286	2522	309	Jagung
Juli	25.1	83.8	55	28	2,407	6278	5805	Kedelai
Agustus	26.3	80.7	70	1	76,962	3444	1534	Padi
September	25.8	81.4	67	191	12,780	3425	2273	Jagung
Oktober	26.9	83.7	57	274	52	6822	6402	Kedelai
November	25.8	89.6	26	928	657	9033	3797	Kacang Tanah
Desember	26.3	85.9	52	372	1,110	2187	1640	Ubi Kayu

From the various data obtained, only a few attributes are used as determinants in generating recommendations. All attributes are numeric, except for the class attribute of the categorical type. The attributes used are as follows.

- RR: Average monthly rainfall (mm) from each district.
- Tavg: The average temperature (° C) per month in each district.
- RH_avg: Humidity (%) used is the average air humidity per month in each district.
- DoS: Length of solar exposure (%) per month from each district.
- Production Results (tons): Total annual production of each district.
- Price (Rp./Kg): Price per kilogram of each commodity in each district.
- Profit (Rp. / Kg): The profit obtained per kilogram from the selling price is reduced by the production costs.
- Plants: Food crop commodities used in this research are rice, corn, soybeans, peanuts, and cassava.

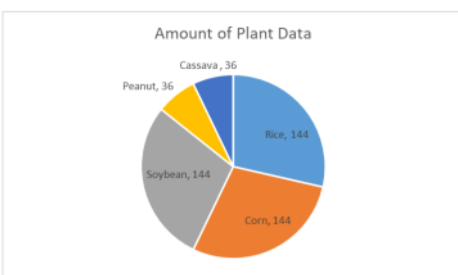

Fig. 4. *Number of Dataset Based on Plant Class*

The data used were 504 data, with five classes. Where each class has a different amount of data such as Figure 1. Rice plants class 144 data, 144 corn data, 144 soybean data, 36 peanut data, and 36 cassava data.

2.4 Naïve Bayes

Naïve Bayes is a simple classifier using knowledge of probability and statistics based on the application of Bayorama Teorama [14]. The Bayorama Teorama equation is as follows [15].

$$P(H|E) = \frac{P(E|H) x P(H)}{P(E)} \quad (1)$$

P(HIE) :	The conditional probability of a hypothesis H occurs if the evidence is provided.
P(EIH) :	The probability that a proof E occurs will affect the hypothesis H.
P(H) :	The initial (prior) hypothesis of H hypothesis occurs regardless of any evidence.
P(E) :	The initial probability (prior) of evidence E occurs regardless of the hypothesis / other evidence.

Generally, Bayes is easily calculated for categorical type features such as in the case of animal classification with the feature "skin cover with value {fur, hair, shell} or case for" sex "feature with value {male, female}. However, for features with numeric (continuous) type there are special treatments before they are included in Naïve Bayes. The method is [15]:

1) Discretizing each continuous feature and replacing the value of the continuous feature with a discrete interval value. This approach is carried out by transforming continuous features into ordinal features or,
2) Assume a certain form of the probability distribution for continuous features and estimate the distribution parameters with training data. The Gaussian distribution is usually chosen to represent the conditional probability of a continuous feature in a class P (Xi I Y), while the Gaussian distribution is characterized by two parameters: mean and variance.

For each class yj, the conditional probability of class yj for feature Xi is :

$$P\ (Xi = xi|Y = yi) = \frac{1}{\sqrt{2\,\pi\,\sigma\,ij}} \exp - \frac{(xi - \mu ij)^2}{2\,\sigma^2\ ij} \quad (2).$$

P	: Opportunity
Xi	: I-th attribute
xi	: I-th attribute value
Y	: Class sought
yi	: Sub-class sought
μ	: mean, average of all attributes
σ	: standard deviation, variants of all attributes

2.5 Performance Testing Method

In this study using the Waikato Environment for Knowledge Analysis (WEKA) to determine the performance of Naïve Bayes in classifying weather data, agriculture, and selling prices to recommend types of food crops. WEKA is a Java-based open-source data mining application. This application was first developed by the University of Waikato in New Zealand before becoming part of Pentaho. Weka consists of a collection of machine learning algorithms that can be used to generalize and formulate a collection of sampling data [16]. WEKA can process regression, classification, clustering, association rules, visualization, and pre-processing [17]. WEKA has been popularly used by various groups and is widely used for teaching. The stages in WEKA are shown in the flowchart of Figure 5.

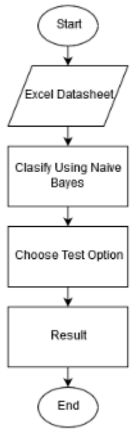

Fig. 5. *WEKA Process Flowchart*

After data collection, then data pre-processing until the data is ready to be processed data is stored in Comma Separated Values (CSV) format. CSV is a format that can be read by WEKA [18]. The next step is to choose the method to be used, in this method using Naive Bayes. To find out how well Naïve Bayes performance needs to be tested, the test used in this study is k-fold cross-validation (k = 10). WEKA will display the results of data testing using the Naïve Bayes method.

2.6 Performance Evaluation

The confusion matrix is obtained after applying the naïve bayes method to the dataset using the WEKA application. All are measured by counting four values namely, TP (True Positive, the amount of positive data that is classified correctly), TN (True Negative, the amount of negative data classified correctly), FP (False Negative, the number of positive data classified incorrectly), FN (False Negative, the amount of negative data is classified incorrectly). In the binary classification type which only has 2 class outputs, the confusion matrix is presented as in Table 3.

TABLE 3

CONFUSION MATRIX

+	TRUE	FALSE
TRUE	*Trues Positif (TP)*	*False Negatif (FN)*
FALSE	*False Positif (FP)*	*True Negatif (TN)*

From the values generated in Table 4 sensitivity, specificity, accuracy, and F1 Score are calculated. Precision is the level of accuracy of the classification results for a condition. The recall is the success rate of recognizing a condition from all conditions and can be calculated using the following equation.

$$Precision = \frac{TP}{(FP + TP)} \quad (3)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (4)$$

Accuracy is defined as the overall level of success of the classifier and is calculated by the following Equation.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + FN + TN)} \quad (5)$$

F1 scores measure accuracy using precision p and recall r. Accuracy is the proportion of true positive (TP) to all predicted positives (TP + FP). Remember is the proportion of true positives for every single actual positive (TP + FN). F1 scores can be calculated using the following equation.

$$F1 = \frac{2TP}{(2TP + FP + FN)} \quad (6)$$

For reference and evaluation, relative mean absolute error (MAE), root mean square error (RMSE), relative absolute error (RAE) and root relative squared error (RMSE) and relative root square error (RMSE) are also calculated.

3 RESULT AND DISCUSSION

The experimental results show the performance of an algorithm [19]. The accuracy and error rate of the algorithm is explained at this stage.

3.1. Data Evaluation and Validation

The evaluation phase is evaluating the performance of an algorithm or method to get the best quality and effectiveness [20]. This step can be used to determine the Naïve Bayes method to predict data in providing crop recommendations. In addition, statistical validation is also needed to verify the performance used to evaluate and validate the dataset. In practice, randomly dividing data as training data and test data based on k-fold cross-validation (k = 10). Training data as a classifier and test data are used to estimate performance classifications [21]. At this stage shows the results of the classification of true and false, the time required, consistency test with kappa statistics shown in Table 4.

TABLE 4

NAÏVE BAYES CLASIFICATION RESULT

Correctly Classified Instances (%)	*Incorrectly Classified Instances (%)*	*Time Taken (s)*	*Kappa Statistic*
85.71%	*14.29%*	*0.06*	*0.8084*

Based on Table 4, the performance of the Naïve Bayes algorithm to provide recommendations for types of food crops has an accuracy of 85.71% and takes 0.06 seconds. The level of consistency is obtained from the Kappa Statistics value of 0.8084. Kappa Statistics is obtained from a comparison of accuracy obtained with random accuracy expected [22].

TABLE 5

ERROR CLASIFICATION RESULT

Mean Absolute Error	*Root Mean Squared Error*	*Relative Absolute Error*	*Root Relative Squared Error*
0.1051	*0.2314*	*35.25%*	*59.96%*

Based on Table 5, the experimental results based on misclassification are Mean Absolute Error of 0.1051, Root Mean Squared Error 0.2314, Relative Absolute Error 35.25%, and Root Relative Squared Error of 59.96%.As a supporter of the results of classification accuracy to evaluate and validate the Naïve Bayes method in classifying food crop types, several previous studies used Precision, Recall, F-Measure, and ROC Area as benchmarks [23]. In this study, the results are shown in Table 6.

TABLE 5

NAÏVE BAYES PERFORMANCE RESULT

Mean Absolute Error	*Root Mean Squared Error*	*Relative Absolute Error*	*Root Relative Squared Error*
0.1051	*0.2314*	*35.25%*	*59.96%*

Precision can be considered as the ability of the model to distinguish data from relevant instances between instances taken, while Recall (also called sensitivity) is the ability of the model to select data from a large population [21].. In addition, the F-Measure is obtained from the Precision and Recall measurements, in general, the range of values given is between 0-1, the closer to 1 the F-Measure results the better the performance of a model. ROC area to measure the performance of various classification models in differentiating classes [6].

3.2. Discussion

Recommendations for types of food crops are very helpful for farmers in an era of climate change that is difficult to predict anymore. Farmers no longer use cropping patterns that have been carried down for generations. The results obtained also depend on natural conditions. The selection of the right types of food plants is expected to improve the economy of farmers. The possibility of farmers experiencing crop failure can be minimized and the yields obtained can increase, and when farmers have harvested the selling price of the crop being harvested is high. These conditions become a treasure for farmers. Therefore, in providing recommendations for food plants must use the right model. By utilizing various factors that influence the recommendation of plant types to be the attributes used in this study. The application of models that have predictive capabilities can provide recommendations for types of food plants. The model used in this study is Naïve Bayes. Based on the results of experiments using WEKA, Naïve Bayes is suitable for use in the dataset recommended for food crops. it is proven by high accuracy values, low error rates, and high-performance results. Therefore, Naïve Bayes can provide recommendations for food crops.

4 CONCLUSION

In this study, we explain the Naïve Bayes method and the reasons why we use the Naïve Bayes method. We focus on designing an effective classifier to classify types of food plants to provide recommendations to farmers based on weather, agricultural products and the selling price of food crops. Based on the test results, the Naïve Bayes method is feasible to use, the performance produced by this method is very good. However, this method still needs to be compared to other methods to find out the best method and can be implemented into a decision support system for farmers in determining crop types.

5 ACKNOWLEDGMENT

The research was funded by the directorate general of higher education, the Ministry of technology research, and higher education Indonesia through the Competitive Research Grant scheme 2019. Contract number 111/SP2H/LT/DRPM/2019 and PT-004/SKPP.TT/LPPM UAD/III/2019.

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