Optimization Of Naïve Bayes Based On Genetic Algorithm For Performance Evaluation Of Lecturers Of PGRI Wiranegara University

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Article Info :	**ABSTRACT**
Article History : Received : 01 July 2022 Revised : 29 July 2022 Accepted : 17 August 2022 Available Online : 25 August 2022 **Keyword :** Performance Evaluation Of Lecturers, Naïve Bayes, Genetic Algorithm, feature selection	*The evaluation of educators' performance, particularly that of professors, is crucial for maintaining the high quality of instruction at the college. This study employed Bayes Methods as the basis for performance assessment, using the criteria set forth by the quality assurance unit's standards of conformity. The results of the Bayes Method will aid the institution in evaluating professors' performance, with the goal of enhancing their skills and serving as a decision-making tool. A Genetic Algorithm (GA) was proposed to optimize the Naïve Bayes parameter value and improve accuracy. The results showed that the accuracy of the Naive Bayes was 89.93%, while the accuracy of the Naive Bayes with Genetic Algorithm was 95%, indicating that the latter method is more effective*

1. INTRODUCTION

Achieving high-quality students requires high-quality learning. Numerous factors contribute to the success of a quality educational process, in accordance with national learning standards. The teaching competency standards are directly related to the teaching and learning process. The quality of the learning process will impact the quality of the graduates. Lecturer performance is a critical component of the college education system. Therefore, identifying patterns and providing support for the development of education and lecturers is of utmost importance to achieve the objectives of the college. The college cannot function without lecturers who provide teaching, conduct research, perform community service, and engage in various other scientific activities

The performance quality of lecturers is established in Indonesian National Education Standard Law No. 14 of 2005. The law contains four competencies for lecturers, including pedagogical competence, personal competence, social competence, and professional competence. These competencies are mandatory for lecturers to become professional educators

Therefore, having professional and high-quality lecturer in higher education institutions is not an easy task. To achieve this, higher education institutions must conduct performance

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evaluations. Performance evaluations are not only necessary in companies and the business world, but also in education

Effective teaching and learning processes can help students achieve their goals according to their abilities and fields of study. High-quality teaching must be evaluated and improved every semester throughout the year. Meanwhile, evaluations must be conducted to assess the effectiveness of the teaching and learning process and used to enhance the professionalism of the professors. Performance evaluations can be used to assess professor competence, such as in the design of teaching and curriculum development based on the National Competency Standards for Higher Education (N. Ketut, 2012)

Based on the explanation above, the performance evaluation of professors at Universitas PGRI Wiranegara has been taking place, but it is still semi-manual and the performance evaluation is not comprehensive. The expected results are not optimal as desired, the collection time for reports is still long, and the evaluation process requires more time and energy, which can hinder its implementation and smoothness. To meet these needs, Data Mining techniques can be used to quickly and accurately evaluate. Data mining plays a role in information gathering to obtain the knowledge contained in the data (Nilesh Choudhary, 2018)

Data Mining is a scientific discipline that studies methods for extracting knowledge or discovering patterns from large sets of data, commonly used in the IT, banking, and agriculture fields. Naive Bayes Classifier (NBC) is a classification algorithm based on Bayes' decision theory that uses probabilities to make decisions. NBC is a simple, effective, fast, highly accurate, and widely used classification algorithm compared to other classification algorithms (Nilesh Choudhary, 2018)

Naive Bayes has several advantages, such as being able to classify or group data based on previous data. An example of this is the classification of emails, which can vary based on the reader's subject. An email classified as not spam by one person may be considered spam by another. Similarly, in the case of evaluating a lecture's performance using the Naive Bayes method, the data can be grouped, meaning that the classification process for the lecture's performance data can be customized based on the needs of each institution or organization (Natalius, 2011)

There have been several researchers who have used the Naive Bayes algorithm. Ajay Kumar Pal and S.Pal (Pal, 2013) conducted a study titled "Evaluation of Teacher's Performance: A Data Mining Approach" and used four classification algorithms. The results showed that Naive Bayes had the highest accuracy among the methods ID3, CART, LAD, and Naive Bayes. Another study by Mujib Ridwan et al. (M. Ridwan, 2013) used the Naive Bayes approach. Cholikul Nur Anwar (Luthfiarta, 2014) used the fuzzy c-mean method. The Naive Bayes classification method has a weakness of being independent, which affects the accuracy of the calculation

The research on lecturer performance can still be improved in terms of accuracy by using optimization. Naive Bayes is a data mining classification algorithm that assumes each attribute is not related or independent, so Genetic Algorithm is used to determine the attribute, thus improving accuracy.

2. METHOD

The research that will be designed to categorize the performance assessment of lecturers in order to determine which lecturers need guidance. In this research, a clear and consistent research method is proposed so that the desired results can be achieved. The testing design model will contain all the stages in the performance assessment categorization of lecturers. This design model will process the training and testing data to test the used algorithm method. The stages to be followed are divided into three parts, preprocessing, feature selection, and validation.

The research method will be tested using the Rapidminer software. The index stage of the lecturer's performance assessment will use the Genetic Algorithm for feature selection, and the

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Naive Bayes Classifier (NBC) as the classification algorithm. The classification stage will undergo 10-fold cross validation to obtain the maximum accuracy value.

The preprocessing stage is a questionnaire that provides a scale for the assessment of lecturer performance. From the preprocessing stage, the performance assessment of lecturers will be weighted. Then the results will be processed using feature selection optimization using the Genetic Algorithm. After going through the feature selection stage, the next step will be classification with the validation stage. To obtain the maximum accuracy value, 10 validations will be used. In addition, the experiment will result in the best confusion matrix produced by Naive Bayes

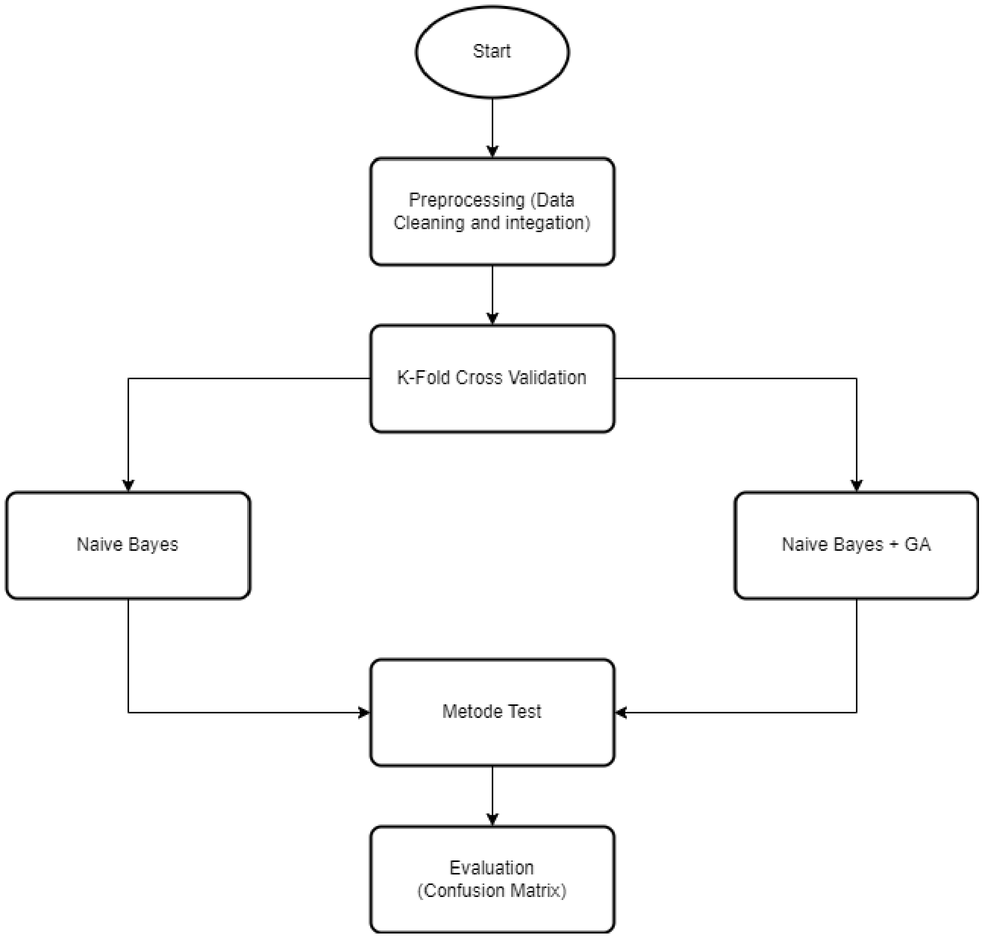

Figure 1. Flowchart of the Classification Process

3. RESULTS AND ANALYSIS

3.1 Pre-processing datasets

Naïve Bayes Classifier is a classification method using the Bayesian theorem as a basis. Naïve Bayes Classifier is a data classification method using probability and statistics. Samples were taken from lecturer performance data from two Faculties at PGRI Wiranegara University

The data source used is a private dataset from PGRI Wiranegara University. The dataset in this study consists of 83 lecturers with 7 attributes. The data used is from the Quality Assurance Unit, and used as attributes, namely:

1. Student Assessment (EK1)
2. Collection of final exam questions (EK2)

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3. Lecturer Attendance (EK3)
4. Leader Assessment (EK4)
5. Lecturer Research (EK5)
6. Community Service (EK6)
7. Final Grade Collection (EK7)

3.2. Naïve Bayes Experimen

The calculation of the prior probability for a class requires the construction of the following formula for calculating the prior probability. The calculation of the prior probability for a class requires the construction of the following formula for calculating the prior probability

$$P(Ci|X)=\frac{P(X|Ci)\ P(Ci)}{P(X)}$$

P(Ci |X) = probability of the hypothesis if given facts or record X (Posterior probability)
P(X|Ci) = looking for value parameter that gives the greatest possibility (likelihood)
P(Ci) = Prior probability of X (Prior probability)
P(X) = Total probability tuple which appears

In this experiment, the probability for class determination is calculated using the NBC formula to calculate lecturers who need coaching (Yes class) with a total of 19 and lecturers who do not need coaching (No class) with a total of 60.
The calculation of the prior probability for the class requiring coaching is as follows, the formula for calculating the prior probability:

$$P(C_i I\mathbf{X}) = \frac{P(\boldsymbol{X} I C i) P(C i)}{P(\boldsymbol{X})}$$

then

$$P(C1): \frac{23}{83} = 0{,}228916$$

While calculating the prior probability for classes that do not require coaching, the formula for calculating the prior probability is :

$$P(C0): \frac{60}{83} = 0{,}722892$$

The following steps determine the probability value on each attribute for both lecturers who do not need coaching and need coaching:

a. Probability for questionnaire score attribute

Table 1. Probability Table of Questionnaire Attributes

Score	Yes	No
Excelent	0.30434782	0.38333333
Good	0.47826087	0.56666667
Fair	0.08695652	0.03333333
Low	0.13043478	0.01666667
Very low	0	0

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The table above explains to calculate each possible result of the questionnaire score criteria, for each possible lecturer who needs coaching. For the calculation of the probability of the above questionnaire attributes as follows:

Calculate P(X|C1) for C1 = "Yes"

- P(questionnaire = ”Excelent” | Description = “Yes”) = $\frac{7}{23} = 0{,}30434782$
- P(questionnaire = ”Good” | Description = “Yes”) = $\frac{11}{23} = 0{,}47826087$
- P(questionnaire = ”Fair” | Description = “Yes”) = $\frac{2}{23} = 0{,}08695652$
- P(questionnaire = ”Low” | Description = “Yes”) = $\frac{3}{23} = 0{,}13043478$
- P(questionnaire = ”Very Low” | Description = “Yes”) = $\frac{0}{23} = 0$

Calculate P(X|C0) untuk C0 = “No”

- P(questionnaire = ”Excelent” | Description = “No”) = $\frac{23}{60} = 0{,}38333333$
- P(questionnaire = ”Good” | Description = “No”) = $\frac{34}{60} = 0{,}56666667$
- P(questionnaire = ”Fair” | Description = “No”) = $\frac{2}{60} = 0{,}03333333$
- P(questionnaire = ”Low” | Description = “No”) = $\frac{1}{60} = 0{,}01666667$
- P(questionnaire = ”Very Low” | Description = “No”) = $\frac{0}{60} = 0$

b. Probability for the attribute of accuracy of collecting exam questions

Table 2. Probability Table of Exam Question Attributes

Value	Yes	No
0	0,57692307	0,42307692
1	0,14035087	0,85964912

The table above explains to calculate each possible result of the accuracy criteria in collecting the final semester exam questions, for each possible lecturer who needs coaching.

Calculate P(X|C1) for C1 = "On Time"

P(Collect Exam Question = "0" | Description = "Yes") = "15"/"26" =0,57692307

P(Collect Exam Question = "1" | Description = "Yes") = "8" /"26" =0,14035087

Calculate P(X|C0) for C0 = "No"

P(Collect Exam Question = "0" | Description = "No") = "11" /"57" =0,42307692

P(Exam Question Collection = "1" | Description = "No") = "49"/"57" =0,85964912

c. Probability for lecturer attendance attribute

Table 3. Probability Table for Lecturer Attendance Attributes

Nilai	Ya	Tidak
4	0,166666667	0,833333333
3	0,206349206	0,793650794
2	0,8	0,2
1	0,25	0,75

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Explanation of the table above to calculate each possible result of the lecturer attendance criteria, for each possible lecturer who needs coaching

Calculate P(X|C1) for C1 = "Yes"

P(Lecturer Attendance Score = "4" | Description = "Yes") = "7"/"63" =0.166666667

P(Lecturer Attendance Score = "3" | Description = "Yes") = "11" /"63" =0.206349206

P(Lecturer Attendance Score = "2" | Description = "Yes") = "2" /"63" =0,8

P(Lecturer Attendance Score = "1" | Description = "Yes") = "3" /"63" =0,25

Calculate P(X|C0) for C0 = "No"

P(Lecturer Attendance Score = "4" | Description = "No") = "5" / "20" =0.83333333333

P(Lecturer Attendance Score = "3" | Description = "No") = "50" / "20" =0.793650794

P(Lecturer Attendance Score = "2" | Description = "No") = "2" /"20" =0.2

P(Lecturer Attendance Score = "1" | Description = "No") = "3" / "20" =0.75

d. Probability for the leader assessment attribute

Table 4. Probability Table for Leader Assessment Attributes

Value	Yes	No
4	0,038461538	0,961538462
3	0,302325581	0,697674419
2	0,692307692	0,307692308
1	0,5	0,5

Explanation of the table above to calculate each possibility of direct assessment from the leader, for each possibility of lecturers who need coaching

Calculate P(X|C1) for C1 = "Yes"

P(Leadership Assessment = "4" | Description = "Yes") = "1"/"26" =0,038461538

P(Leader Assessment = "3" | Description = "Yes") = "13" /"43" =0,302325581

P(Leader Assessment = "2" | Description = "Yes") = "9"/"13" =0,692307692

P(Leader Assessment = "1" | Description = "Yes") = "1"/"2" =0.5

Calculate P(X|C0) for C0 = "No"

P(Leader Rating = "4" | Description = "No") = "5" /"20" =0.961538462

P(Leader Rating = "3" | Description = "No") = "50" / "20" =0.697674419

P(Leader Rating = "2" | Description = "No") = "2" /"20" =0.307692308

P(Leader Assessment = "1" | Description = "No") = "3" /"20" =0.5

e. Probability for research attributes that have been done by lecturers

Table 5. Research Attribute Probability Table

Value	Yes	No
1	0.142857143	0.857142857
2	0.31884058	0.68115942

Explanation of the table above to calculate each possibility of research that has been done, for each possible lecturer who needs coaching

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ISSN Online : 2541-1942

Calculate P(X|C1) for C1 = "On time"

P(Collect Exam Question = "0" | Description = "Yes") = "15"/"26" =0,57692307

P(Collect Exam Question = "1" | Description = "Yes") = "8" /"26" =0,14035087

Calculate P(X|C0) for C0 = "No"

P(Collect Exam Question = "0" | Description = "No") = "11" /"57" =0,42307692

P(Exam Question Collection = "1" | Description = "No") = "49"/"57" =0,85964912

f. Probability for the attribute of service that has been done by lecturers

Table 6. Probability Table of Service Attributes

Value	Yes	No
1	0,098039216	0,901960784
2	0,59375	0,40625

In the table above to calculate each possibility of service that has been done by lecturers, for each possibility of lecturers who need coaching

Calculate P(X|C1) for C1 = "Yes"

P(Devotion = "0" | Description = "Yes") = "15"/"26" =0,098039216

P(Service = "1" | Description = "Yes") = "8"/"26" =0,59375

Calculate P(X|C0) for C0 = "No"

P(Devotion = "0" | Description = "No") = "11"/"57" =0,901960784

P(Devotion = "1" | Description = "No") = "49"/"57" =0,40625

g. Probability for the test score collection attribute

Table 7. Probability Table for Exam Grade Collection Attribute

Nilai	Ya	Tidak
0	0,354166667	0,645833333
1	0,171428571	0,828571429

In the table above to calculate each probability of collecting exam grades, for each possible lecturer who needs coaching.

Calculate P(X|C1) for C1 = "Yes"

P(Exam Grade Collection = "0" | Description = "Yes") = "15"/"26" =0,354166667

P(Gathered Exam Score = "1" | Description = "Yes") = "8" /"26" =0,171428571

Calculate P(X|C0) for C0 = "No"

P(Collect Exam Score = "0" | Remarks = "No") = "11" /"57" =0,645833333

P(Gathered Exam Score = "1" | Description = "No") = "49"/"57" =0,828571429

3.3 Naïve Bayes Experiment With The Tool

The following will discuss the naïve bayes experiment without using Genetic Algorithm with a dataset containing the assessment of 83 lecturers with 7 attributes using k-fold validation 10 times. After the process is done, the testing data and training data will come out the accuracy results.

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Table 8. Number of Validation Naïve Bayes Testing

Sampling type	Number of Validation	Accuracy	AUC
Stratified Sampling	2	76,92%	0,826
Stratified Sampling	3	89,93%	0,862
Stratified Sampling	4	79,66%	0,848
Stratified Sampling	5	84,75%	0,877
Stratified Sampling	6	84,75%	0,833
Stratified Sampling	7	81,36%	0,894
Stratified Sampling	8	84,75%	0,888
Stratified Sampling	9	84,75%	0,848
Stratified Sampling	10	86,44%	0,870

In the test table above, the highest value is selected at the 2nd number of validation with stratified sampling type with an accuracy value of 89.93%, AUC 0.862 and the lowest accuracy value at the 2nd number of validation of stratified sampling type with an accuracy value of 76.92%.

Table 9. Experiments with Shuffled sampling type

Sampling type	Number of Validation	Accuracy	AUC
Shuffled Sampling	2	86,44%	0,838
Shuffled Sampling	3	69,49%	0,828
Shuffled Sampling	4	77,97%	0,842
Shuffled Sampling	5	83,05%	0,857
Shuffled Sampling	6	77,97%	0,870
Shuffled Sampling	7	83,05%	Unknown
Shuffled Sampling	8	83,05%	Unknown
Shuffled Sampling	9	81,36%	Unknown
Shuffled Sampling	10	84,75%	Unknown

From the use of shuffled sampling type, the highest accuracy value at the 2nd number of validation is 86.44% and AUC 0.838 while the lowest value at shuffled sampling is 69.49% and AUC 0.828.

Table 10. Experiments with Linear Sampling type

Sampling type	Number of Validation	Accuracy	AUC
Linear Sampling	2	84,75%	0,869
Linear Sampling	3	88,12%	0,847
Linear Sampling	4	88,14%	0,892
Linear Sampling	5	77,97%	0,866
Linear Sampling	6	84,75%	Unknown
Linear Sampling	7	79,66%	Unknown
Linear Sampling	8	83,05%	Unknown
Linear Sampling	9	81,36%	Unknown
Linear Sampling	10	84,75%	Unknown

In the table above, the naïve bayes test was conducted with linear sampling type for the highest accuracy value of 88.14% and AUC 0.892 at the 4th number of validation while the lowest accuracy value was 77.97% at the 5th number of validation with an accuracy value of 77.97% and AUC value of 0.866.

When conducting the third experiment, three samplings were applied Linear Sampling, Shuffled Sampling, Stratified Sampling as shown in the table below.

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Table 3.11 Three types of Sampling Experiments for the Naive Bayes Algorithm

Sampling Type	Number Of Validations	Accuracy	AUC
Stratified sampling	3	89,93%	0,862
Linear Sampling	4	88,14%	0,892
Shuffled Sampling	2	86,44%	0,838

Table 3.12 Naïve Bayes Experiment Based on Genetic Algorithm

Sampling Type	Number Of Validations	Accuracy	AUC
Stratified sampling	10	95,00%	0,904
Linear Sampling	10	95,00%	0,904
Shuffled Sampling	10	95,00%	0,904

3.4 Confusion Matrix

In measurements using the naïve bayes method and Genetic Algorithm using confusion matrix, the results of the classification process are 4 (four). True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). True Negative (TN) is the amount of negative data detected, while false positive (FP) is negative data but detected as positive data. Meanwhile, True positive (TP) is positive data that is detected correctly. False Negative (FN) is the opposite of true positive, so the data is positive but detected as negative data.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{57+3}{57+3+3+16} = 0{,}8993 \text{ x } 100\% = 89{,}93\ \%$$

$$Precision \text{ Yes} = \frac{TP}{TP+FN} = \frac{57}{57+16} = 0{,}780822 \text{ x } 100\% = 78{,}08\ \%$$

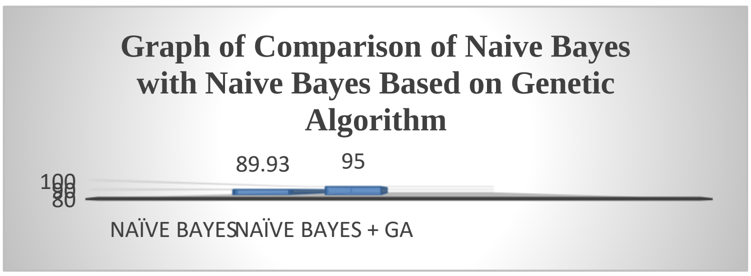
$$Precision \text{ No} = \frac{TN}{TP+FP} = \frac{3}{57+3} = 0{,}05 \text{ x } 100\% = 5{,}00\ \%$$

Table 3.13 Confusion Matrix results of Naive Bayes and Genetic Algorithm testing

Genetic Algorithm

	True “No”	True “Yes”	Class Precision
Prediction No	57	3	95%
Prediction *Yes*	3	16	84,21%
Class Recall	95%	84,21%	

The accuracy rate of Naive Bayes is 89.93% versus 95.00% if it is optimized with the Genetic Algorithm, the difference or increase is 5.07 while the AUC Naïve Bayes is 0.862 compared to 0.904, so there is an increase of 0.042 which will be illustrated in the graph below:



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4. CONCLUSION

In testing lecturer performance evaluation data using the Naïve Bayes Algorithm, it was obtained with an accuracy value of 89.93%, which means that it proves that the Naïve Bayes algorithm is very suitable for data classification.

From the tests carried out by the naïve Bayes classification based on Genetic Algorithm with a result of 95% there was an increase of 5.07% so this could be used as a model to be applied to other cases.

5. DECLARATION OF COMPETING INTEREST

We declare that we have no conflict of interest.

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