The Automatic Classification System for Academic Performance Evaluation at the Faculty of Information Technology Atma Jaya University of Makassar

Erick Alfons Lisangan[1], Dwi Marisa Midyanti[2], Chairul Mukmin[3], Astrid Lestari Tungadi[4]

[1]*Computer Science study program, Atma Jaya University of Makassar, Makassar, Indonesia*
[2]*Computer System study program, Tanjungpura University, Pontianak, Indonesia*
[3]*Computer Science study program, Bina Darma University, Palembang, Indonesia*
[4]*Information System study program, Atma Jaya University of Makassar, Makassar, Indonesia*

[1]erick_lisangan@lecturer.uajm.ac.id, [2]dwi.marisa@siskom.untan.ac.id, [3]chairul.mukmin@binadarma.ac.id, [4]astrid_tungadi@lecturer.uajm.ac.id

Abstract - The Faculty of Information Technology currently carries out performance evaluations at the end of each semester and involves students as sources of data evaluation. The evaluation activity took place online on the website ss.fti.uajm.ac.id. With the number of active students, the number of evaluations that need to be read and the number read by faculty stakeholders also increases. This is inversely proportional to the time that stakeholders need time to read, evaluate, and categorize comments entered by students as part of the performance evaluation. In this study, a multi-classification of student comments related to evaluations at the Faculty of Information Technology UAJM will be carried out. Text pre-processing will use the Sastrawi library which includes stopword removal, stemming, and transformation of text into TFIDF form. The results of the pre-processing text will be used as input on Naive Bayes and using three scenarios to evaluate the classifier model. The average accuracy values of the Naive Bayes algorithm for category and sentiment labels are 79% and 81%, respectively. Furthermore, the expected result of this research is to reduce the time for FTI UAJM stakeholders to read and comment/suggest faster because the evaluation results are obtained in real-time.

Keywords: Naive Bayes Classifier, Sastrawi library, evaluation system, academic performance

I. INTRODUCTION

The Faculty of Information Technology (FTI) is one of the faculties at Atma Jaya Makassar University (UAJM). FTI has 2 (two) study programs, namely Informatics Engineering and Information Systems. As one of the Study Program Management Units (UPPS), the operational process follows the standards set by the National Accreditation Board for Higher Education (BAN-PT). One of the activities that must be carried out is evaluating the performance of UPPS. This is intended as part of improving the performance of UPPS so that periodic quality improvements are achieved.

FTI as UPPS currently carries out performance evaluation activities at the end of each semester and involves students as a source of evaluation data. The evaluation activity took place online on the website ss.fti.uajm.ac.id. Students will be asked to input the performance evaluation in 2 (two) forms, namely the performance evaluation based on the satisfaction scale value (poor to very good) and comments for suggestions (Fig. 1). The evaluation results are then used as input for top-level management, such as the Dean, Deputy Dean, and Head of Study Programs, as a basis for making decisions for future improvements. In addition, the results of the evaluation are then used as the basis for preparing the budget for the next academic year.

In Fig. 2 based on Data Base of Ministry of Education, Culture, Research, and Technology Republic of Indonesia in 2021, it can be seen the number of FTI UAJM students for the last 2 years with an average of around 149 students. In line with the number of active students, the number of evaluations that need to be read and evaluated by FTI stakeholders is also increasing. This is inversely proportional to the working time they have due to the high workload of stakeholders to complete job duties. Based on this, a problem was identified, namely that stakeholders needed time to read, evaluate, and categorize comments/suggestions entered by students as part of the performance evaluation. Based on the identification results, a problem is obtained, namely how to help stakeholders in FTI UAJM to be able to evaluate comments/suggestions quickly so that the decision-making process can be carried out properly. One solution that can be given to solve these problems is to use a classification system model to categorize comments and suggestions given by students automatically.

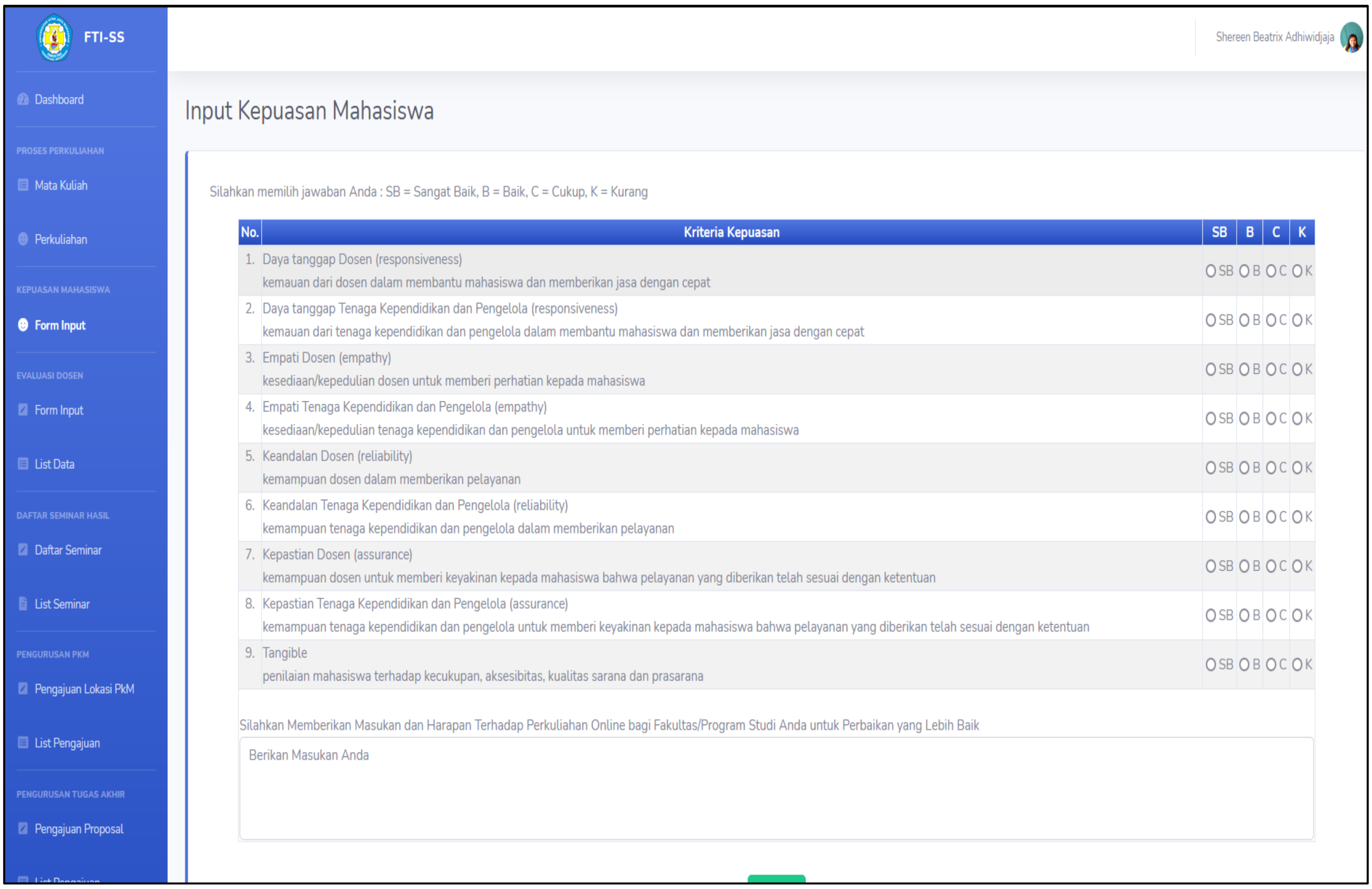


Fig. 1 Performance evaluation input form

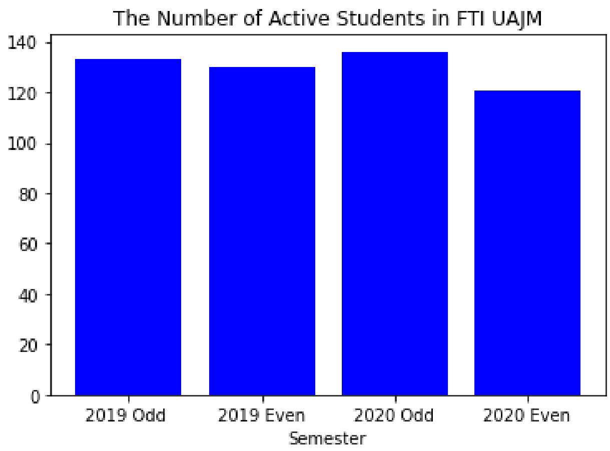


Fig. 2 Graph of the number of active students of FTI UAJM

Many studies related to text-based classification systems have been found at this time as in [1]–[5]. Reference [1] implemented the Naive Bayes algorithm to classify complaints and community reports automatically. The data used was obtained through the National Police Service 110 which is one of the services provided by the Indonesian National Police to assist with problems concerning public order and security through a telecommunications network based at the Indonesian National Police Headquarters located in South Jakarta. The results showed that The Naive Bayes Classifiers method could classify complaints and public reports with a high average accuracy, namely 93% recall, 90% precision, and 92% f-measure. In [2] implemented an algorithm to classify online news related to narcotics abuse. A total of 225 data were collected from online news consisting of several factors, namely individual factors, environment, and drugs. The results showed that the algorithm's performance was quite good with a recall value of 75.8%, precision of 97.7%, and accuracy of 96.4%. In [3] implemented the Naive Bayes algorithm to predict the satisfaction level of Indonesian e-ID Card recording services by using 17 indicators. The accuracy of the classifier model was 91.70% and the research tried to compare it with the decision tree algorithm with 65.90% accuracy.

Reference [4] analyzed the word weighting method combined with the Naive Bayes algorithm. The word weighting method used is TF, IDF, RF, TF-IDF, TF.RF, TF.CHI, and WIDF. The results showed that the combination of TF.RF and Naive Bayes was the best with 98.67% Accuracy, 93.81% Precision, and 96.67% Recall. In [5] the Sastrawi library was implemented as a stemming to do text preprocessing on student complaint data. Based on the results of the study, it can be seen that the Sastrawi library shows stemming results reaching 92% in the Exact Match category compared to Porter Stemming.

Naive Bayes is a classification-based classification algorithm that is simple and effectively implemented for words in independent documents [6]- [7] and has been widely used for text-based classification, such as opinion classification [8], cyberbullying detection [9], and sentiment analysis [10]. The use of Naive Bayes to evaluate academic performance has been investigated previously in the scope of evaluating student performance [11]–[13], academic services [14], and student learning styles [15]. In this study, data in the form of booleans (Yes or No), numbers (semester IP scores), to categories (gender) are used as attributes of decision-making in evaluating academic performance.

In this study, a multi-classification of student comments related to performance evaluation at the Faculty of Information Technology UAJM will be carried out. Text pre-processing will use the Sastrawi library which includes the process of stopword removal, stemming, and text transformation into TFIDF form. The results of the pre-processing text will be used as input to the Naive Bayes algorithm to conduct training on the training data. The class labels given are the performance category and comment sentiment. The results of the research are expected to be able to speed up reading the results of comments by stakeholders.

II. METHOD

A. *Classification Model*

The design of the performance evaluation classification model (Fig. 3) consists of a case-folding process, stopword removal, TF-IDF vectorizing, and the Naive Bayes Classifier algorithm. Case folding is a step to convert all letters in a document into lowercase letters where only the letters 'a' to 'z' are used. Stopword Removal is the process of filtering or selecting any words used to represent documents. TF-IDF stands for Term Frequency Inverse Document Frequency. TF-IDF is a very common algorithm for converting text into a meaningful number representation which is used to adapt engine algorithms for prediction. The stages of weighting with TF-IDF are as follows [16] - [17]:

- Calculate the term frequency $tf_{t,d}$ by comparing the number of occurrences of a word with the total number of words in a document.
- Calculate the weighting term frequency or term frequency weight ($Wtf_{t,d}$) using (1)

$$Wtf_{t,d} = 1 + \log tf_{t,d} \quad (1)$$

- Calculate the document frequency (df) or the number of document frequencies containing the term
- Calculate the weight of the inverse document frequency (idf) using (2) where N is the total number of documents

$$idf_t = \log \frac{N}{df_t} \quad (2)$$

- Calculate the TF-IDF weight value using (3) where $W_{t,d}$ is the TF-IDF weight

$$W_{t,d} = Wtf_{t,d} + idf_t \quad (3)$$

The naive Bayes algorithm or often called Naive Bayes classifier (NBC) is one of the algorithms in the classification method that can predict the probability or possibility of membership in a class [18]. NBC assumes attribute values in a class are independent or independent of values in other attributes. The general equation of NBC can be seen in equation (1). The basis of Naïve Bayes used in programming is the Bayes formula in (4). The probability of the occurrence of A being B or P(A | B) is determined from the probability of B when A or P(B | A), the probability of A or P(A), and the probability of B or P(B) [19].

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \quad (4)$$

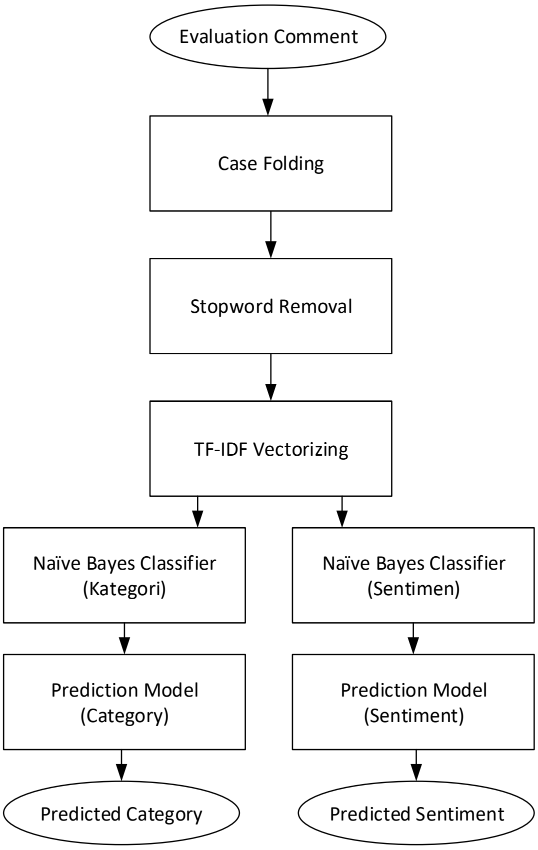


Fig. 3 Design of classification model

Measurement of the results of the classification method Naïve Bayes Classifier used Confusion Matrix. The confusion matrix (Fig. 4) is a method used to perform accurate calculations on the concept of data mining. Evaluation with the confusion matrix produces several values, namely precision (proportion of positive predicted cases that are also true positives on the actual data), recall (proportion of actual positive cases that are correctly predicted positive), and accuracy (percentage of accuracy of data records classified individually). correct after testing on the classification results) [20], each of which can be seen in (5) (6), and (7).

$$Precision = TP / (TP + FP) \quad (5)$$

$$Recall = TP / (TP + FN) \quad (6)$$

$$Accuracy = (TP + TN) / (TP + FP + FN + TN) \quad (7)$$

B. Data Collecting

The data used in this study is evaluation data/suggestions from students in the Early Semester of 2019/2020 to the Final Semester of 2020/2021 or 4 (four) semesters. The source of evaluation data is obtained from the internal information system of FTI UAJM which uses a MySQL database as a data storage application. The dataset is converted to CSV format to facilitate data processing which can be seen in Fig. 5.

Based on the evaluation data obtained from the period of the Early Semester of 2019/2020 to the Final Semester of 2020/2021, a total of 416 records can be obtained. The structure of the academic service performance evaluation data consisting of 4 (four) attributes can be seen in Table I.

C. Data Preparation

The evaluation dataset is then given a category label and comment sentiment based on the input given by the students. The comment categories used are Facilities and Performance. While the sentiment comments used are Satisfied and Dissatisfied. In Fig. 5 it can be seen that there are records where the evaluation attribute is not filled in by students or has missing values. The Random Sample Imputer method [21] was used to replace the missing data with a random sample taken from the variables in the training set. The results of filling in the missing values can be seen in Fig. 6 where the distribution of data for the Facilities and Performance categories is 101 and 315 and Satisfied and Dissatisfied sentiments are 172 and 244. The distribution of data can be seen in Fig. 7.

TABLE I
DATA STRUCTURE OF ACADEMIC PERFORMANCE EVALUATION

No.	Attribute	Data Type	Description
1.	Student ID	String	Student ID
2.	Semester	Category	Semester code
3.	Year	Integer	Semester year
4.	Judgement	String	Student's comments or suggestions

		Actual Class	
		Positive (**P**)	Negative (**N**)
Predicted Class	Positive (**P**)	True Positive (**TP**)	False Positive (**FP**)
	Negative (**N**)	False Negative (**FN**)	True Negative (**TN**)

Fig. 4 Confusion matrix

Student ID	Semester	Year	Judgement
1861003	AW	2019	Mohon fasilitas agar lebih diperhatikan.
1861028	AW	2019	
1863002	AW	2019	
1861022	AW	2019	Lebih ditingkatkan lagi
1861004	AW	2019	
1961008	AW	2019	Lebih di tingkatkan soal kedisplinan waktu pengajaran. Masuk tepat waktu dan keluar tepat wakt
1961015	AW	2019	
1961009	AW	2019	Lebih ditingkatkan kedisiplinan...
1961012	AW	2019	
1961005	AW	2019	
1961018	AW	2019	
1961019	AW	2019	
1961014	AW	2019	
1963006	AW	2019	
1961003	AW	2019	
1961023	AW	2019	
1963003	AW	2019	
1961007	AW	2019	
1861001	AW	2019	
1963002	AW	2019	
1661008	AW	2019	
1661002	AW	2019	
1861012	AW	2019	
1661012	AW	2019	
1761009	AW	2019	fasilitas pada fakultas kurang, sehingga membuat pembelajaran berlangsung kurang nyaman. pro
1661006	AW	2019	
1763008	AW	2019	
1661017	AW	2019	turunkan sedikit standar penilaian tugas akhir
1661003	AW	2019	
1763005	AW	2019	
1861005	AW	2019	Mungkin jika ada kesusahan pada mahasiswa, dosen dapat memberikan tugas untuk membantu r
1661016	AW	2019	
1661014	AW	2019	
1861027	AW	2019	tdk ada

Fig. 5 Academic performance evaluation data in CSV format

	Student ID	Semester	Year	Judgement	Category	Sentiment
0	1861003	AW	2019	Mohon fasilitas agar lebih diperhatikan.	Facility	Dissatisfied
1	1861028	AW	2019	NaN	NaN	NaN
2	1863002	AW	2019	NaN	NaN	NaN
3	1861022	AW	2019	Lebih ditingkatkan lagi	Performance	Dissatisfied
4	1861004	AW	2019	NaN	NaN	NaN

```
dataset_train.shape
```

```
(416, 6)
```

Fig. 6 Final dataset after Random Sample Imputer to handle missing value

III. RESULT AND DISCUSSION

After going through the text pre-processing stage, 416 data were then divided into training data and test data with three scenarios, that is a proportion of 70%:30% for Scenario I (Fig. 8), 75%:25% for Scenario II (Fig. 9), and 80%:20% for Scenario III (Fig. 10). The text pre-processing process uses the Sastrawi library and the implementation of the Naive Bayes algorithm uses the Python programming language.

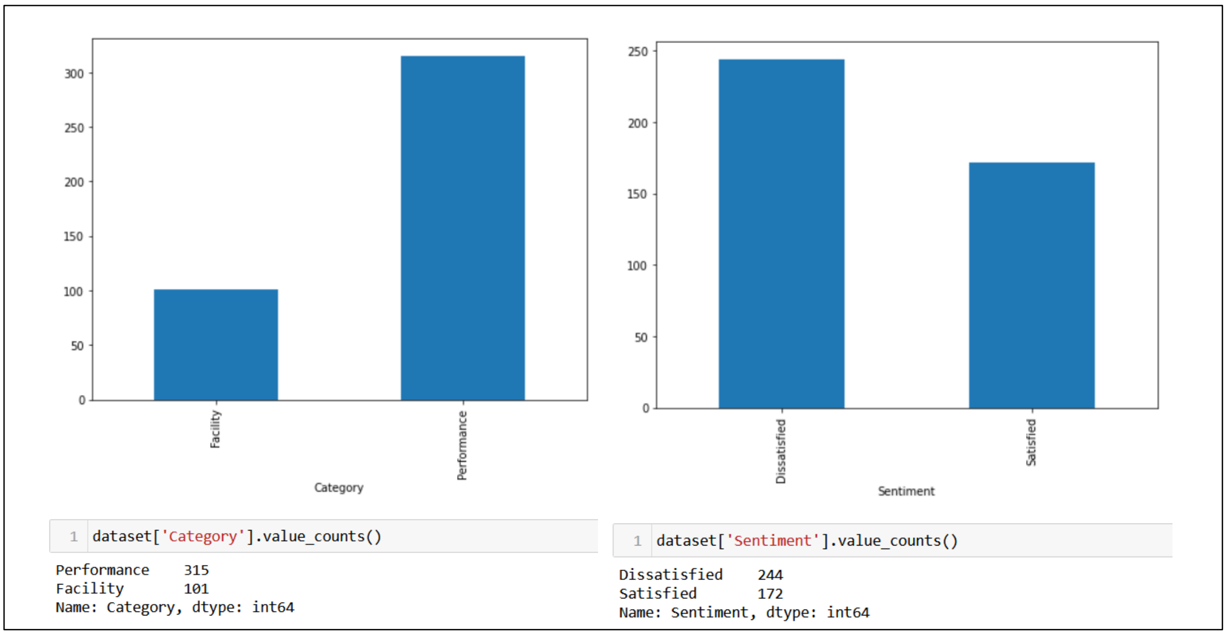


Fig. 7 Data distribution of comments based on Category and Sentiment labels

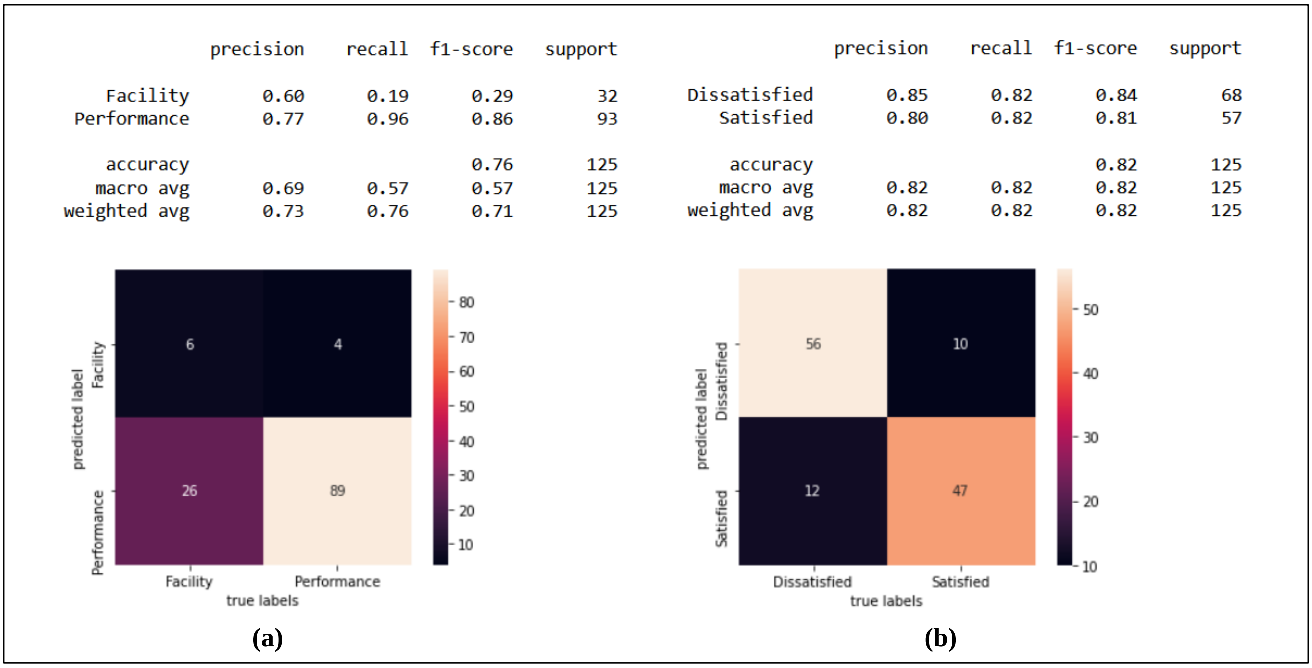


Fig. 8 Confusion matrix of Category (a) and Sentiment (b) for Scenario I

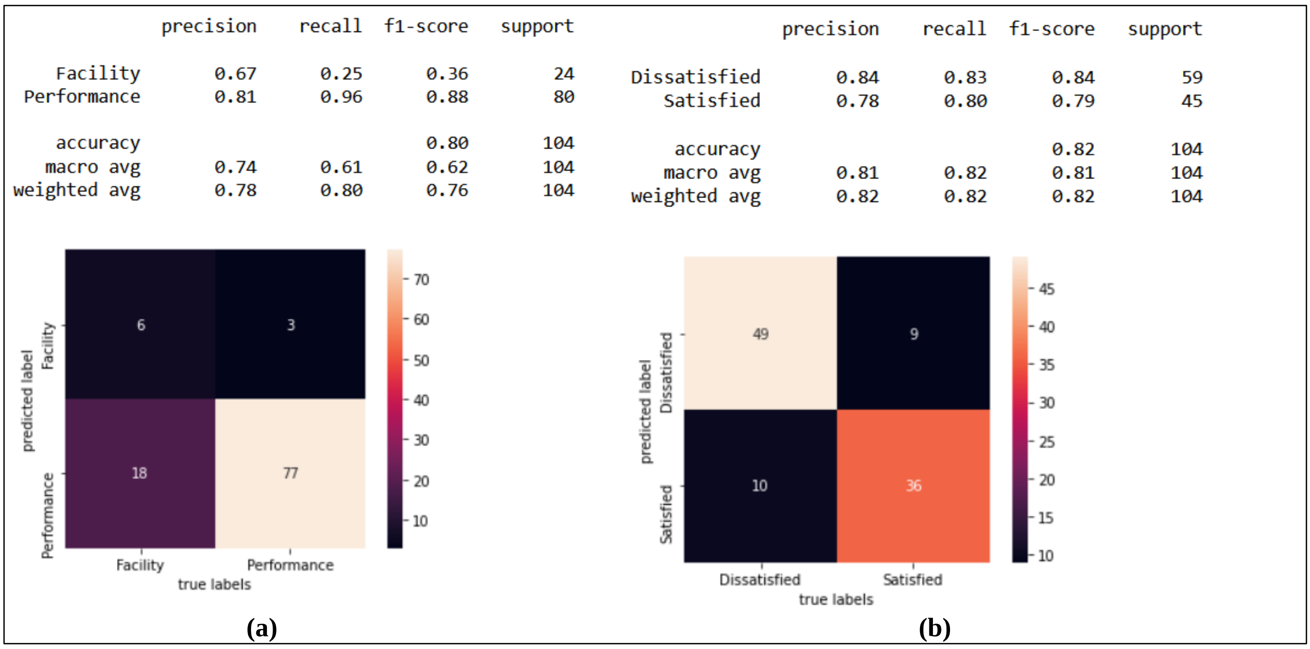
Fig. 8 is the result of the confusion matrix for Category and Sentiment label test data for Scenario I with 70% of training data (291 data) and 30% of testing data (125 data). For illustration, several values for the result of Facility Category can be obtained based on Fig. 8a, that is TP = 6, FP = 4, FN = 26, TN = 89. Moreover, several evaluation values can be summarized, that is:

Precision = TP / (TP + FP) = 6 / (6 + 4) = 6/10 = 0.60

Recall = TP / (TP + FN) = 6 / (6 + 26) = 6/32 = 0.19

Accuracy = (TP + TN) / (TP + FP + FN + TN) = (6 + 89) / (6 + 4 + 26 + 89) = 95/125 = 0.76

The accuracy obtained for Category labels using the Naïve Bayes Classifier is 0.76, or 95 data out of 125 data can be recognized by true class. On the other hand, with the same equation, the accuracy for Sentiment labels is 0.82 that means 103 data can be recognized in the true class out of 125 testing data.



	precision	recall	f1-score	support
Facility	0.67	0.25	0.36	24
Performance	0.81	0.96	0.88	80
accuracy			0.80	104
macro avg	0.74	0.61	0.62	104
weighted avg	0.78	0.80	0.76	104

	precision	recall	f1-score	support
Dissatisfied	0.84	0.83	0.84	59
Satisfied	0.78	0.80	0.79	45
accuracy			0.82	104
macro avg	0.81	0.82	0.81	104
weighted avg	0.82	0.82	0.82	104

Fig. 9 Confusion matrix of Category (a) and Sentiment (b) for Scenario II

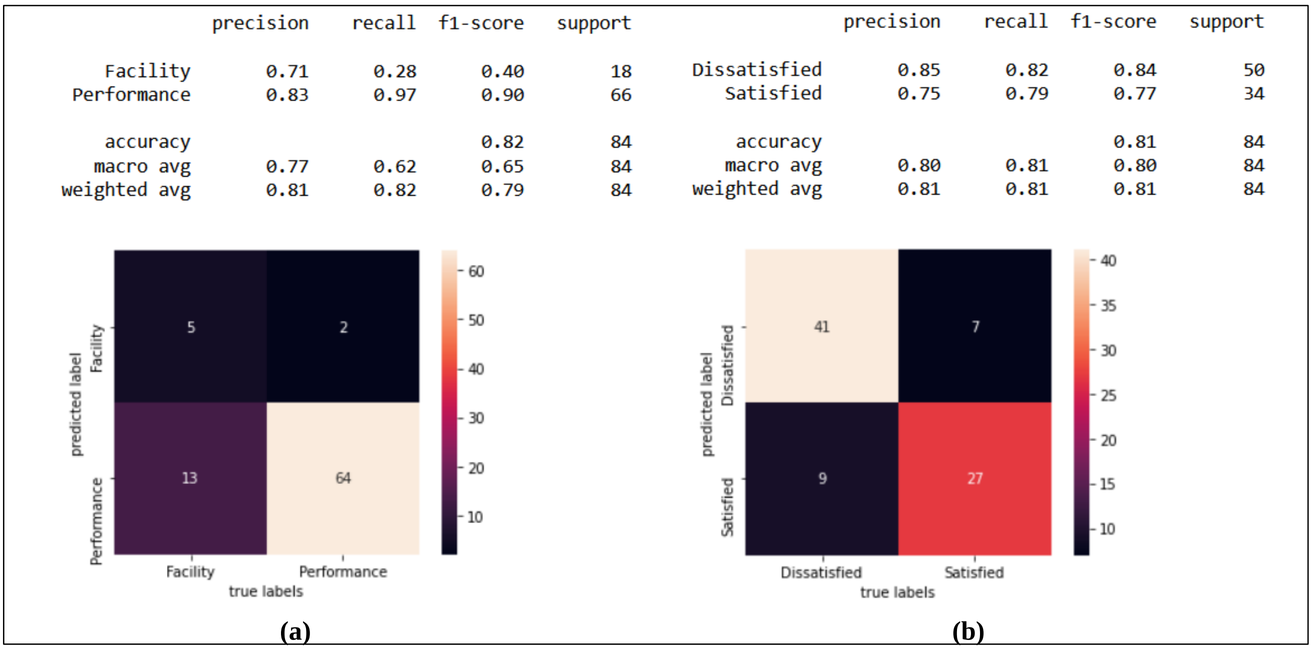
Fig. 9 is the result of the confusion matrix for Category and Sentiment label test data for Scenario II with 75% of training data (312 data) and 30% of testing data (104 data). For illustration, several values for the result of Facility Category can be obtained based on Fig. 9a, that is TP = 6, FP = 3, FN = 18, TN = 77. Moreover, several evaluation values can be summarized, that is:

Precision = TP / (TP + FP) = 6 / (6 + 3) = 6/9 = 0.67

Recall = TP / (TP + FN) = 6 / (6 + 18) = 6/24 = 0.25

Accuracy = (TP + TN) / (TP + FP + FN + TN) = (6 + 77) / (6 + 3 + 18 + 77) = 83/104 = 0.80

The accuracy obtained for Category labels using the Naïve Bayes Classifier is 0.80, or 83 data out of 104 data can be recognized by true class. On the other hand, with the same actions, the accuracy for Sentiment labels is 0.82 that means 85 data can be recognized in the true class out of 104 testing data.



	precision	recall	f1-score	support
Facility	0.71	0.28	0.40	18
Performance	0.83	0.97	0.90	66
accuracy			0.82	84
macro avg	0.77	0.62	0.65	84
weighted avg	0.81	0.82	0.79	84

	precision	recall	f1-score	support
Dissatisfied	0.85	0.82	0.84	50
Satisfied	0.75	0.79	0.77	34
accuracy			0.81	84
macro avg	0.80	0.81	0.80	84
weighted avg	0.81	0.81	0.81	84

Fig. 10 Confusion matrix of Category (a) and Sentiment (b) for Scenario III

The result of the confusion matrix for Category and Sentiment label test data for Scenario III with 80% of training data (332 data) and 20% of testing data (84 data) can be seen in Fig. 10. For illustration, several values for the result of Facility Category can be obtained based on Fig. 10a, that is TP = 5, FP = 2, FN = 13, TN = 64. Furthermore, several evaluation values can be summarized, that is:

Precision = TP / (TP + FP) = 5 / (5 + 2) = 5/7 = 0.71
Recall = TP / (TP + FN) = 5 / (5 + 13) = 5/18 = 0.28
Accuracy = (TP + TN) / (TP + FP + FN + TN) = (5 + 64) / (5 + 2 + 13 + 64) = 69/84 = 0.82

The accuracy obtained for Category labels using the Naïve Bayes Classifier is 0.82, or 69 data out of 84 data can be recognized by true class. On the other hand, with the same actions, the accuracy for Sentiment labels is 0.81 that means 68 data can be recognized in the true class out of 84 testing data. The summarize of the evaluation model for three scenarios can be seen in Table II and Table III.

The summarization results of the confusion matrix in Table 2 and Table 3 shows that the classification results for sentiment labels do not have the same problems as category labels. In Table 3, the average of precision, recall, and accuracy is in stable values, with approximately 0.82, for three scenarios. This is because the distribution of data for category labels (Fig. 7) is quite balanced with a ratio of 172 and 244 for satisfied and dissatisfied categories. However, in Table 2 it can be seen that the average value of precision and recall value of the Category label is in the range of values below 0.8. As it can be seen that the minimum value of recall is very low with 0.19, 0.25, and 0.28 for three scenarios, which means that the proportion for data with the label classified correctly is only a little data compared to the remaining data are incorrectly classified into the false label. This is because the distribution of data (Fig. 7) for category labels is imbalanced where performance labels are more dominant so that the chance of a data being classified into a performance category is greater.

Based on this result, it can be said that Naive Bayes Classifier is very sensitive with the imbalanced data. However, it still can get the good result and performance with an accuracy value above 0.8 for Scenario II and III in both of Category and Sentiment label and could become the process model to support the evaluation system. The main reason is because the algorithm works by calculated the probability for each word and the possible classes. Still, the implementation of the others classification methods, such as Support Vector Machine, k-Nearest Neighbour, is required in the future works as a comparison with Naïve Bayes Classifier's result.

After the model is deemed to have a fairly high average accuracy, where 79% for category labels and 81% for sentiment labels, then the application design is carried out using the PHP, ClearDB, python, and Heroku services platforms. The infrastructure design can be seen in Fig. 11.

Fig. 11 Design of system infrastructure

TABLE II
THE EVALUATION MODEL OF CATEGORY LABEL FOR THREE SCENARIOS

No.	Scenario	Precision		Recall		Accuracy
		Average	Minimum	Average	Minimum	
1.	Scenario I	0.69	0.60	0.57	0.19	0.76
2.	Scenario II	0.74	0.67	0.61	0.25	0.80
3.	Scenario III	0.77	0.71	0.62	0.28	0.82
	Average	**0.73**		**0.60**		**0.79**

TABLE III
THE EVALUATION MODEL OF SENTIMENT LABEL FOR THREE SCENARIOS

No.	Scenario	Precision		Recall		Accuracy
		Average	Minimum	Average	Minimum	
1.	Scenario I	0.82	0.80	0.82	0.82	0.81
2.	Scenario II	0.81	0.78	0.82	0.80	0.82
3.	Scenario III	0.80	0.75	0.81	0.79	0.81
	Average	**0.81**		**0.82**		**0.81**

After logging in, students can see the input form to write comments/suggestions while attending lectures at FTI UAJM. Fig. 11 is a student satisfaction input form page. The results of inputting input from students will be processed using a model that has been designed and evaluated so that the input will be labelled as belonging to which category and sentiment automatically. The classifier model will help to make an automatic classification for students' comment and suggestion. The result will help the stakeholder of faculty to summarize and make a decision more quickly and accurate.

IV. CONCLUSION

Based on the research that has been done, several conclusions can be concluded that the use of the Naive Bayes Classifier algorithm produces a fairly good average accuracy value for each label and sentiment category with a value of 79% and 81%. Naive Bayes Classifier is very sensitive with the imbalanced data. However, it still can get the good result and performance because the algorithm works by calculated the probability for each word and the possible classes. Furthermore, an automatic evaluation system is designed that has been designed to provide significant benefits where the evaluation results can be seen in real-time compared to conditions where decisions need to be evaluated manually. Suggestions that can be given in this study are the need for improvement in the classification of category labels because there are imbalanced data. This causes the value of precision and recalls to be low with values of 0.73 and 0.60. Improvements in data classification are expected to be able to improve algorithm performance so that even better accuracy is produced.

REFERENCES

[1] F. Handayani and S. Pribadi, "Implementasi Algoritma Naive Bayes Classifier dalam Pengklasifikasian Teks Otomatis Pengaduan dan Pelaporan Masyarakat melalui Layanan Call Center 110," *J. Tek. Elektro*, vol. 7, no. 1, pp. 19–24, 2015, doi: https://doi.org/10.15294/jte.v7i1.8585.

[2] O. Arifin, "Sistem Klasifikasi Berita Daring Faktor Kejahatan Penyalahgunaan Narkotika Berbasis Algoritma Naive Bayes," *Telematika*, vol. 11, no. 2, p. 27, 2018, doi: 10.35671/telematika.v11i2.713.

[3] T. H. Apandi and C. A. Sugianto, "Algoritma Naive Bayes untuk Prediksi Kepuasan Pelayanan Perekaman e-KTP," *JUITA J. Inform.*, vol. 7, no. 2, p. 125, 2019, doi: 10.30595/juita.v7i2.3608.

[4] A. Deolika, K. Kusrini, and E. T. Luthfi, "Analisis Pembobotan Kata Pada Klasifikasi Text Mining," *J. Teknol. Inf.*, vol. 3, no. 2, p. 179, 2019, doi: 10.36294/jurti.v3i2.1077.

[5] M. A. Rosid, A. S. Fitrani, I. R. I. Astutik, N. I. Mulloh, and H. A. Gozali, "Improving Text Preprocessing for Student Complaint Document Classification Using Sastrawi," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 874, no. 1, 2020, doi: 10.1088/1757-899X/874/1/012017.

[6] R. M. Chezian and C. Kanakalakshmi, "Performance Evaluation of Machine Learning Techniques for Text Classification," in *UGC Sponsored National Conference on Advanced Networking and Applications*, 2015, no. March, pp. 53–57.

[7] N. Nagajothi and A. R. Nadira Banu Kamal, "Analysing performance of text classification models for sentiment analysis of movie reviews," *Int. J. Sci. Technol. Res.*, vol. 9, no. 2, pp. 3788–3791, 2020.

[8] H. Irsyad and M. R. Pribadi, "Klasifikasi Opini Terhadap Pertanian Sawit (Palm Oil) Indonesia Menggunakan Naïve Bayes," *JATISI (Jurnal Tek. Inform. dan Sist. Informasi)*, vol. 6, no. 2, pp. 230–239, 2020, doi: 10.35957/jatisi.v6i2.182.

[9] I. Y. Anggraini, S. Sucipto, and R. Indriati, "Cyberbullying Detection Modelling at Twitter Social Networking," *JUITA J. Inform.*, vol. 6, no. 2, p. 113, 2018, doi: 10.30595/juita.v6i2.3350.

[10] E. A. Lisangan, A. Gormantara, and R. Y. Carolus, "Implementasi Naive Bayes pada Analisis Sentimen Opini Masyarakat di Twitter Terhadap Kondisi New Normal di Indonesia," *KONSTELASI Konvergensi Teknol. dan Sist. Inf.*, vol. 2, no. 1, pp. 23–32, 2022, doi: 10.24002/konstelasi.v2i1.5609.

[11] M. Ridwan, H. Suyono, and M. Sarosa, "Penerapan Data Mining Untuk Evaluasi Kinerja Akademik Mahasiswa Menggunakan Algoritma Naive Bayes Classifier," *Eeccis*, vol. 7, no. 1, pp. 59–64, 2013, doi: 10.1038/hdy.2009.180.

[12] E. Prasetyowati and N. Ramadhani, "Sistem Evaluasi Dan Klasifikasi Kinerja Akademik Mahasiswa Universitas Madura Menggunakan Naive Bayes Dengan Dirichlet Smoothing," *JUTI J. Ilm. Teknol. Inf.*, vol. 16, no. 2, p. 192, 2018, doi: 10.12962/j24068535.v16i2.a688.

[13] R. Rachmatika and A. Bisri, "Perbandingan Model Klasifikasi untuk Evaluasi Kinerja Akademik Mahasiswa," *J. Edukasi dan Penelit. Inform.*, vol. 6, no. 3, p. 417, 2020, doi: 10.26418/jp.v6i3.43097.

[14] K. A. Aeni, "Prediksi Kepuasan Layanan Akademik Menggunakan Algoritma Naïve Bayes," *JATISI (Jurnal Tek. Inform. dan Sist. Informasi)*, vol. 7, no. 3, pp. 601–609, 2020, doi: 10.35957/jatisi.v7i3.603.

[15] N. Hidayat and L. Afuan, "Naïve Bayes for Detecting Student's Learning Style Using Felder-Silverman Index," *JUITA J. Inform.*, vol. 9, no. 2, p. 181, 2021, doi: 10.30595/juita.v9i2.10191.

[16] W. A. Luqyana, I. Cholissodin, and R. S. Perdana,

"Analisis Sentimen Cyberbullying pada Komentar Instagram dengan Metode Klasifikasi Support Vector Machine," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 2, no. 11, pp. 4704–4713, 2018, [Online]. Available: http://j-ptiik.ub.ac.id.

[17] N. K. Widyasanti, I. K. G. Darma Putra, and N. K. Dwi Rusjayanthi, "Seleksi Fitur Bobot Kata dengan Metode TFIDF untuk Ringkasan Bahasa Indonesia," *J. Ilm. Merpati (Menara Penelit. Akad. Teknol. Informasi)*, vol. 6, no. 2, p. 119, 2018, doi: 10.24843/jim.2018.v06.i02.p06.

[18] B. Syamsul, M. Dwi, and H. Rahmi, "Perbandingan Algoritma Naive Bayes dan C4.5 Untuk Klasifikasi Penyakit Anak," *Semin. Nas. Apl. Teknol. Inf.*, pp. B24–B31, 2018.

[19] S. Lorena., "Teknik Data Mining Menggunakan Metode Bayes Classifier Untuk Optimalisasi Pencarian Aplikasi Perpustakaan," *J. Tek. Komput.*, vol. 4, no. 2, pp. 17–20, 2016.

[20] S. Adinugroho and Y. A. Sari, *Implementasi Data Mining Menggunakan Weka*. Malang: Universitas Brawijaya Press, 2018.

[21] P. D. Allison, "Handling Missing Data by Maximum Likelihood," *SAS Glob. Forum 2012 Stat. Data Anal.*, pp. 1–21, 2012.