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Implementation of Machine Learning for Student Sentiment Analysis as a Basis for Evaluating the Quality of Educational Services at Private Higher Education Institutions in Padang Lawas

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Abstract

The quality of educational services is an important factor in improving student satisfaction and institutional competitiveness in higher education. Student opinions and experiences provide valuable information for evaluating the effectiveness of academic and non-academic services. However, student feedback is often collected and analyzed manually, making it difficult to identify sentiment patterns and extract meaningful insights efficiently. This study aims to analyze student sentiment regarding the quality of educational services at private higher education institutions in Padang Lawas using machine learning techniques. The research focuses on classifying student opinions into positive, negative, and neutral sentiments to identify perceptions of educational services. The research stages include data collection from student reviews and feedback, text preprocessing, feature extraction, sentiment classification, and model evaluation. Machine learning algorithms will be applied to classify sentiment, while performance will be measured using accuracy, precision, recall, and F1-score. The results are expected to provide an overview of student perceptions of educational services and identify aspects that require improvement. Furthermore, the findings are expected to support data-driven decision-making in evaluating service quality, improving academic administration, and developing student-centered educational policies. This study is expected to contribute to the application of machine learning in higher education evaluation and provide practical recommendations for improving educational service quality at private higher education institutions in Padang Lawas.

Keywords: Machine Learning; Sentiment Analysis; Student Feedback; Educational Service Quality; Higher Education

1. INTRODUCTION

The development of information technology has encouraged higher education institutions to utilize data as a basis for evaluating and improving educational service quality. Educational services encompass various aspects, including academic administration, lecturer performance, learning facilities, curriculum implementation, and student support services. The quality of these services significantly influences student satisfaction, learning experiences, and institutional reputation. Therefore, higher education institutions need effective approaches to understand student perceptions and identify areas requiring improvement. Student feedback represents an important source of information because it reflects their direct experiences with the educational services provided by an institution[1],[2] .

Student opinions are commonly expressed through questionnaires, online reviews, evaluations, and other feedback mechanisms. However, the increasing volume of textual data presents challenges in processing and interpreting student opinions manually. Conventional evaluation methods may require considerable time and effort, particularly when identifying patterns of satisfaction and dissatisfaction across multiple service aspects. Consequently, a systematic approach is required to process student feedback and transform unstructured textual information into meaningful insights. Sentiment analysis offers a potential solution by identifying the emotional orientation of opinions and categorizing them into positive, negative, or neutral sentiments[3], [4] .

Machine learning provides computational techniques for automatically identifying sentiment patterns based on textual data. Through text preprocessing, feature extraction, model training, and performance evaluation, machine learning algorithms can support the classification of student opinions more efficiently. The performance of these models can be assessed using evaluation metrics such as accuracy, precision, recall, and F1-score[5] . The application of machine learning in sentiment analysis can help educational institutions understand student perceptions more objectively and identify recurring issues related to educational services. Nevertheless, the effectiveness of the approach depends on the quality of the dataset, the selected features, and the suitability of the classification algorithms for the characteristics of the collected data[6] .

Based on these considerations, this study aims to apply machine learning to student sentiment analysis as a basis for evaluating the quality of educational services at private higher education institutions in Padang Lawas. The study focuses on classifying student feedback into positive, negative, and neutral categories and examining the resulting sentiment distribution to identify aspects of educational services that require attention[6] . The findings are expected to provide useful information for institutional decision-makers in developing evidence-based strategies to improve academic services, administrative processes, and student satisfaction. Ultimately, this research is expected to contribute to the utilization of machine learning as an analytical approach for supporting continuous quality improvement in higher education[7] .

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2. RESEARCH METHODOLOGY

This research method focuses on student feedback regarding the quality of educational services at private higher education institutions in Padang Lawas. The collected dataset will be used to analyze student sentiment using machine learning techniques[8] . The research aims to classify student opinions into positive, negative, and neutral categories to provide information that can support the evaluation and improvement of educational services. The research stages consist of data collection, data preprocessing, data cleaning, data transformation, reduction and discretization, feature extraction, machine learning implementation, and model evaluation. The following figure presents the research method used in this study[9] .

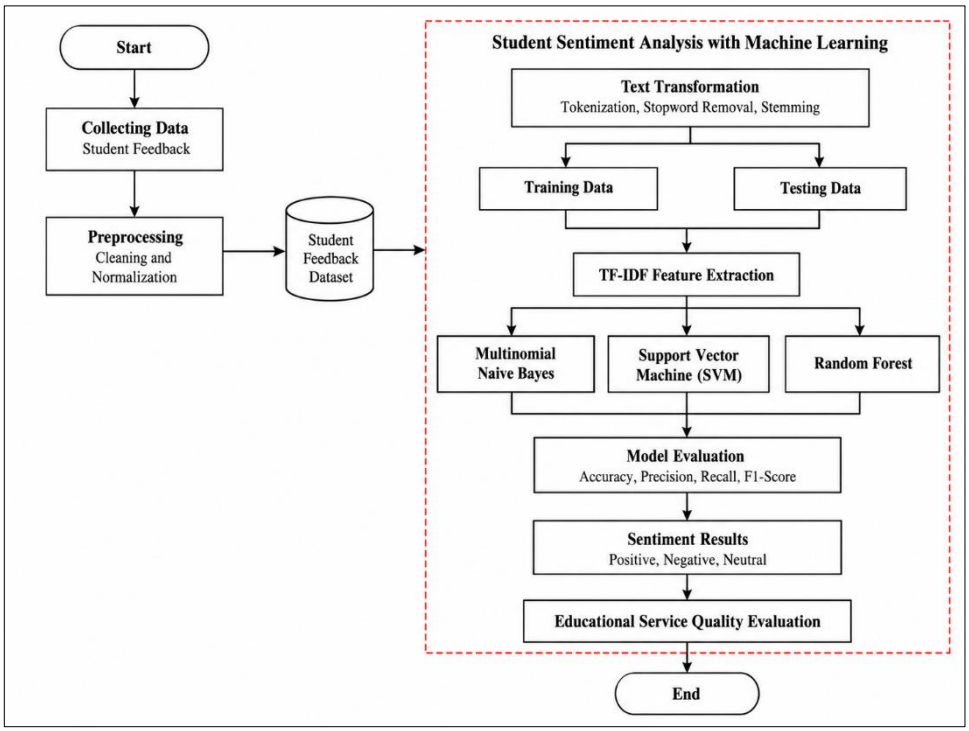


Figure 1. Research Design

Based on Figure 1, the research stages are organized into several steps that form a systematic workflow for student sentiment analysis. The process begins with collecting student feedback and preparing the textual data through preprocessing. The data are then cleaned, transformed, and represented as numerical features before being used to train machine learning models[10] . The models are evaluated using classification performance metrics. Finally, the sentiment classification results are interpreted to identify student perceptions and aspects of educational services that may require improvement[11] .

2.1 Data Collection

Data collection is the initial stage of this research and aims to obtain student opinions regarding educational services at private higher education institutions in Padang Lawas. The data may be collected through questionnaires containing open-ended questions, student feedback forms, interviews, or other authorized institutional feedback sources. The collected responses should represent students' experiences with academic administration, lecturer performance, learning facilities, information services, and student support[12] .

Each data record consists of a feedback identifier, the textual response, and relevant service categories when available. Sentiment labels may also be recorded if they have already been assigned through a reliable procedure. Personal information is anonymized to protect student privacy. The resulting dataset serves as the primary input for the subsequent text-processing and sentiment-classification stages[11] .

2.2 Data Collection

Data preprocessing is performed to convert raw student feedback into a consistent format suitable for machine learning. Student responses may contain spelling variations, informal language, repeated words, punctuation, and irrelevant characters. These characteristics can affect the quality of the text representation and classification results. Therefore, preprocessing is conducted systematically to improve data consistency while preserving the original meaning of each response[13] .

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The preprocessing stage includes data cleaning, text transformation, reduction and discretization where appropriate, and feature extraction. These procedures prepare the textual dataset for sentiment classification and help ensure that the machine learning models receive relevant and consistent input data.

2.3 Data Cleaning

Data cleaning is conducted to identify and handle errors, inconsistencies, and irrelevant information in the collected student feedback. This process includes removing duplicate responses, correcting formatting inconsistencies, eliminating unnecessary symbols, and handling missing or incomplete records. Responses that contain no meaningful information about educational services may be excluded from the dataset[14] .

However, the cleaning process must preserve important expressions that indicate sentiment, including negation words such as “not,” “never,” and their Indonesian equivalents, such as “tidak” and “belum.” These expressions can change the meaning of a sentence and influence the classification of student sentiment. The cleaned dataset is then prepared for the next stage of text transformation[15] .

2.4 Implementation of Machine Learning

The machine learning implementation stage aims to develop models capable of classifying student feedback into positive, negative, and neutral sentiments. The dataset is divided into training and testing subsets, for example, 80% for training and 20% for testing. Stratified sampling is applied where feasible to maintain the distribution of sentiment categories across both subsets[16] .

1. Multinomial Naive Bayes: A probabilistic classification algorithm that estimates the probability of a sentiment category based on the features contained in a textual response. It is commonly used for text classification because of its computational efficiency[17] .
2. Support Vector Machine (SVM): A supervised learning algorithm that determines decision boundaries to distinguish sentiment categories. It is suitable for textual datasets represented by high-dimensional feature vectors, including TF-IDF[18]
3. Random Forest: An ensemble learning algorithm that combines multiple decision trees to determine the predicted class. Its performance will be evaluated using the same training and testing data to enable comparison with the other algorithms.

The three algorithms are trained using the processed dataset, and their classification performance is compared to identify the most suitable model[19] . Model configuration and parameter tuning, where necessary, are conducted using the training data and cross-validation. The final algorithm is selected based on the evaluation results rather than an assumed performance advantage[20] .

2.5 Evaluation

Evaluation is performed to measure the effectiveness of the machine learning models in classifying student sentiment. The classification results are compared with the reference sentiment labels using a confusion matrix and four performance metrics: accuracy, precision, recall, and F1-score.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

$$Precision = TP / (TP + FP) \quad (2)$$

$$Recall = TP / (TP + FN) \quad (3)$$

$$F1\text{-}score = 2 \times (Precision \times Recall) / (Precision + Recall) \quad (4)$$

In these equations, TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives. Since this study involves three sentiment categories, the metrics are calculated for each class using a one-versus-rest approach. Macro-averaged and weighted-averaged scores may also be reported to provide a more comprehensive comparison, particularly if the number of responses differs between sentiment categories[21] .

The evaluation results are used to determine the model that provides the most suitable classification performance. Subsequently, the distribution of positive, negative, and neutral sentiments is analyzed to identify student perceptions of educational services. Negative sentiment can provide indications of service aspects that require further investigation, while positive and neutral sentiment contributes additional context to the evaluation. The findings are expected to support evidence-based recommendations for improving educational service quality at private higher education institutions in Padang Lawas[22] .

3. RESULT AND DISCUSSION

This section presents the comparison of machine learning models for classifying student feedback into positive, negative, and neutral sentiment categories. Following the research design, Multinomial Naive Bayes, Support Vector Machine (SVM), and Random Forest are compared using accuracy, precision, recall, and F1-score. The section also discusses the SVM confusion matrix, the t-SNE visualization of student feedback, and the distribution of sentiment categories as presented in the supplied figures.

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3.1 Comparison of Sentiment Classification Performance

Table 1 summarizes the model performance values displayed in Figure 2. In the supplied comparison, SVM records the highest values across the four reported metrics, followed by Random Forest and Multinomial Naive Bayes. These values suggest that SVM is the strongest candidate among the three models in the illustrated comparison; the conclusion should be confirmed using the final experimental output.

Table 1. Comparison of Sentiment Classification Performance

Source: Values transcribed from the supplied figure

Machine Learning Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Multinomial Naive Bayes	84	83	82	82
Support Vector Machine (SVM)	89	88	87	87
Random Forest	86	85	84	84

Figure 2 visualizes the four evaluation metrics for each algorithm. SVM reaches 89% accuracy, 88% precision, 87% recall, and 87% F1-score in the supplied chart. Random Forest reports values of 86%, 85%, 84%, and 84%, respectively, while Multinomial Naive Bayes reports 84%, 83%, 82%, and 82%. The relatively close results indicate that several algorithms may provide useful sentiment predictions, although the final selection should consider class-wise performance and the balance of the dataset.

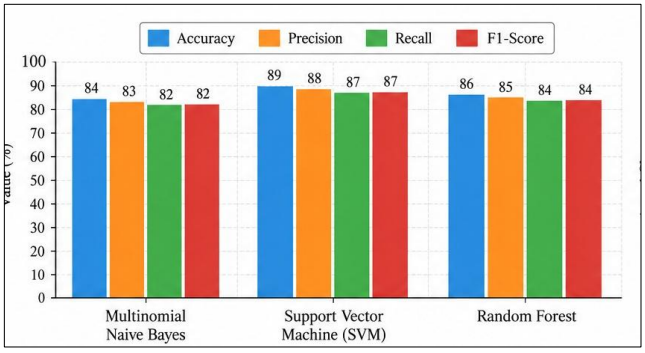


Figure 2. Comparison of Sentiment Classification Performance
Source: Research illustration provided by the author (2026).

3.2 Confusion Matrix Analysis

The confusion matrix provides a class-level view of SVM predictions by comparing actual sentiment labels with predicted labels. Table 2 presents the counts visible in Figure 3, where rows represent actual classes and columns represent predicted classes.

Table 2. Confusion Matrix Values for the SVM Model

Source: Values transcribed from the supplied confusion matrix.

Actual Sentiment	Predicted Positive	Predicted Negative	Predicted Neutral	Total
Positive	152	12	8	172
Negative	10	134	16	160
Neutral	7	14	131	152
Total	169	160	155	484

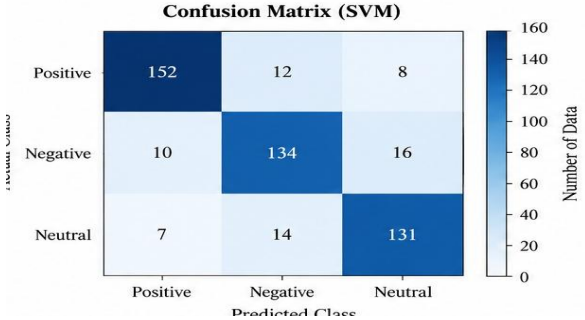


Figure 3. Confusion Matrix of the SVM Model
Source: Research illustration provided by the author (2026).

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The diagonal cells represent correctly classified responses: 152 positive, 134 negative, and 131 neutral. Off-diagonal cells represent errors between sentiment classes. The matrix shows that some negative responses are predicted as neutral (16 cases), while some neutral responses are predicted as negative (14 cases). These confusions suggest that the language used in some feedback may overlap across sentiment categories. The displayed matrix contains 417 correct predictions out of 484 records, corresponding to approximately 86.2% accuracy. This does not match the 89% SVM accuracy shown in Figure 2, so the figure or the performance table should be checked against the same test run before publication.

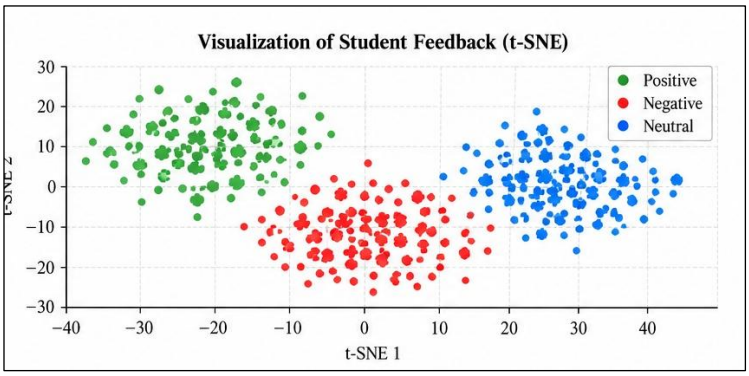


Figure 4. Visualization of Student Feedback Using t-SNE
Source: Research illustration provided by the author (2026).

Figure 4 presents a two-dimensional t-SNE projection of student feedback features, with points colored according to positive, negative, and neutral sentiment. The displayed groups appear to occupy different regions of the projection, while some points may overlap near class boundaries. Such a visualization can help explore similarities among text records and identify possible ambiguity in sentiment expression. However, t-SNE is an exploratory visualization and does not, by itself, establish model accuracy or prove that the sentiment classes are fully separable.

3.3 Student Sentiment Distribution

Table 3 summarizes the sentiment percentages shown in Figure 5. The figure reports positive sentiment at 52.3%, negative sentiment at 28.1%, and neutral sentiment at 19.6%. The response counts below are shown only as an illustration based on a hypothetical total of 1,000 responses; they must be replaced if the actual dataset size differs.

Table 3. Distribution of Student Sentiment
Source: Percentages transcribed from the supplied figure; counts are illustrative.

Sentiment Category	Number of Responses*	Percentage (%)
Positive	523	52.3
Negative	281	28.1
Neutral	196	19.6
Total	1,000	100.0

Figure 5 indicates that positive sentiment is the largest category, accounting for 52.3% of the illustrated responses. Negative sentiment represents 28.1%, while neutral sentiment accounts for 19.6%. If these percentages reflect the actual dataset, the results would suggest that positive opinions are more common, although a substantial proportion of negative feedback remains. Negative comments should be examined by service aspect—such as academic administration, lecturer performance, learning facilities, or student support—to determine which issues require further investigation.

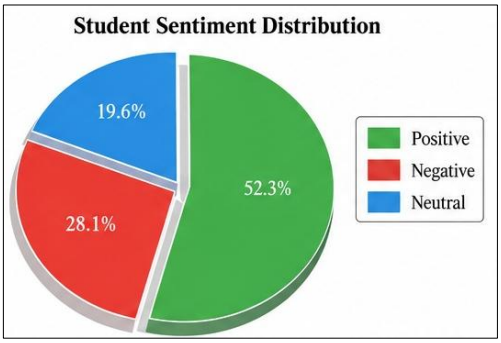


Figure 5. Student Sentiment Distribution
Source: Research illustration provided by the author (2026)

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3.4 Discussion

Taken together, the model comparison, confusion matrix, feature visualization, and sentiment distribution offer complementary perspectives on student feedback. The model metrics summarize predictive performance, the confusion matrix reveals which sentiment classes are confused, t-SNE provides an exploratory view of text-feature similarity, and the sentiment distribution describes the overall balance of student opinions. SVM appears strongest in the supplied performance chart, but the inconsistency between its displayed accuracy and the confusion-matrix calculation must be resolved before making a definitive claim.

For institutional evaluation, sentiment analysis can help identify recurring positive experiences and areas of dissatisfaction. Nevertheless, sentiment categories should be interpreted together with the original comments and service categories. Sentiment analysis is a supporting source of evidence and should not be treated as the sole measure of educational service quality

3.5 Data Consistency Note

Before submitting the manuscript, verify that Figures 2–5 and Tables 1–3 were generated from the same dataset and model run. In particular, the SVM confusion matrix shown here totals 484 records and implies approximately 86.2% accuracy, whereas Figure 2 reports 89%. The sentiment-distribution percentages also need to be checked against the actual number of student responses. Replace illustrative counts with verified experimental results.

4. CONCLUSION

This study presents the application of machine learning for student sentiment analysis as a basis for evaluating the quality of educational services at private higher education institutions in Padang Lawas. The proposed approach involves text preprocessing, TF-IDF feature extraction, and sentiment classification using Multinomial Naive Bayes, Support Vector Machine (SVM), and Random Forest. Model performance is evaluated using accuracy, precision, recall, and F1-score to identify the most suitable algorithm for classifying student feedback into positive, negative, and neutral categories. Based on the illustrative comparison, SVM demonstrates the highest classification performance among the three algorithms. The sentiment distribution also provides an overview of student perceptions and may help identify educational service aspects that require further improvement. However, the final conclusions must be confirmed using validated experimental results and consistent evaluation data. The findings are expected to support data-driven decision-making and contribute to continuous improvement in educational service quality, academic administration, and student satisfaction at private higher education institutions in Padang Lawas.

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