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Assessing Academic Information System Performance Through Sentiment Analysis

[1]Zafira Thuraya, [2]Ali Ibrahim*, [3]Yadi Utama, [4]Dwi Rosa Indah
[1,3,4]Information System, Faculty of Computer Science, Sriwijaya University, Indonesia
[2]Master of Computer Science, Faculty of Computer Science, Sriwijaya University, Indonesia
[1,2,3,4]Jl. Palembang-Prabumulih, KM 32 Inderalaya, Kab. Ogan Ilir, Sumatera Selatan, Indonesia
*e-mail: aliibrahim@unsri.ac.id

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Abstract

The Academic Information System (SIMAK) at Sriwijaya University plays a crucial role in facilitating student academic activities; however, it faces several technical issues that affect user satisfaction, including server outages and challenges in data access. This dissatisfaction serves as a vital metric for evaluating the system's effectiveness. This study aims to analyze student sentiment regarding SIMAK utilizing the Naïve Bayes method. A total of 92 tweets were gathered from Twitter through web scraping, which were then categorized into manually labeled training and test datasets for model validation. The data underwent processing that included text cleaning and the application of Term Frequency-Inverse Document Frequency (TF-IDF) to assess the significance of words within a collection of documents. The evaluation results indicated that the model achieved an accuracy of 65%, with a precision of 63% for negative sentiment and a recall of 100%. In contrast, positive sentiment exhibited a low precision of 12.5% and an F1-score of 22.2%, highlighting difficulties in identifying positive sentiment due to data imbalance. The model demonstrated greater effectiveness in identifying user grievances, particularly concerning server disruptions, data delays, and challenges in completing Study Plan Cards and accessing grades. These findings provide valuable insights for SIMAK maintainers to enhance system reliability and user experience. Future research should aim to broaden data coverage and explore alternative analytical methods to yield more representative outcomes.

Keywords: information system, sentiment analysis, naïve bayes, social media, twitter

1 Introduction

According to data from Reportal, internet usage in Indonesia has reached 185.3 million individuals, reflecting an increase of approximately 1.8% or 5,35 million people over the past year [1]. The integration of the internet within educational institutions presents significant opportunities for the advancement of digital learning in Indonesia, including innovations in both the learning and evaluation processes [2]. One notable application of the internet in higher education is the Academic Information System (SIMAK), which facilitates access to information and communication among students, faculty, and administrative staff [3].

Universitas Sriwijaya has developed SIMAK through its internal IT team to enhance the management of student academic data [4]. This system serves various academic purposes, such as filling out the study plan card , accessing grades on the study result card , and reviewing academic transcripts [5]. However, in practice, several challenges persist, including incomplete information, a less intuitive interface, difficult navigation, delays in data updates, and technical disruptions that hinder the user experience [6]. These issues may affect student satisfaction with SIMAK, ultimately impacting the overall effectiveness of academic services. Therefore, it is essential to conduct evaluations based on student feedback to gain insights into their perceptions of this system.

To assess the extent to which SIMAK meets the needs of its users, an analysis of the services provided is essential for system improvement. In the digital age, social media has emerged as a primary platform for students to express their opinions and experiences, particularly regarding academic services [7]. One frequently utilized platform is X (formerly known as Twitter), which allows users to publish tweets containing text, images, videos, or links [8]. With its extensive user base and role in public discourse, X serves as a relevant data source for various analyses, including sentiment analysis related to academic services in higher education [9].

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Sentiment analysis is a widely employed method for examining textual data, such as comments, reviews, tweets, forums, and articles [10]. In this study, the Naïve Bayes method is utilized as the primary approach to analyze student opinions regarding SIMAK. This algorithm operates on the principle of probability, where the Naïve Bayes model identifies the highest probability values to accurately categorize test data [11].

Previous research has demonstrated that the Naïve Bayes method has been successfully applied in various sentiment analysis contexts. For instance, a study examining public opinion on Google Playstore regarding MyBlueBird application reported a Naïve Bayes model accuracy of 92% [12]. Another study compared this method with the Decision Tree algorithm in analyzing sentiment from users of the Government-issued COVID vaccine where Naïve Bayes achieved an accuracy of 85%, surpassing Decision Tree, which recorded 78%[13]. However, these studies primarily focused on social issues and healthcare services, while sentiment analysis related to academic information systems, particularly at Universitas Sriwijaya, remains underexplored.

This study aims to analyze student sentiment toward SIMAK, the academic information system of Universitas Sriwijaya, utilizing the Naïve Bayes method. The study specifically investigates student perceptions derived from data gathered on Twitter, a topic that has not been extensively studied in prior research. The findings contribute to a clearer understanding of the SIMAK user experience, based on student feedback.

2 Literature Review

Research conducted by Tri et al. utilized a questionnaire as a source of sentiment data. The objective of this study was to classify student opinions regarding instructors based on various factors, including mastery of the subject matter, explanation skills, teaching methods, punctuality, and other relevant aspects. This research employed the Naïve Bayes Classifier to categorize student sentiments as positive, negative, or neutral. The outcome of this study is a web-based system that presents a summary of the instructor questionnaires, accessible at any time and from any location [14]

Another study was carried out by focusing on the Academic Information System at the Garut Institute of Technology [15]. This research aimed to assess user sentiment towards the SIAM application to assist developers in enhancing the system. However, the research methodology was not elaborated upon in detail, and the study primarily highlighted the tools utilized. The findings indicated that positive sentiment accounted for 57.14%, negative sentiment for 37.14%, and neutral sentiment for 5.71%, which were visualized in the form of a word cloud.

Additionally, Dualu et al. investigated the sentiment classification of students regarding the Academic Information System (SIAKAD) at STIMIKOM Stella Maris Sumba. This system is accessible to students, staff, and faculty for academic purposes. Data were collected through a questionnaire, yielding 112 comments, of which 62 expressed positive sentiment. This research employed the Naïve Bayes algorithm with RapidMiner as the software tool, and the testing results demonstrated an accuracy rate of 95.38% [16]

Furthermore, Luqma et al. conducted a study on the SIAM at Brawijaya University using the K-Nearest Neighbor algorithm with feature selection via the Chi-square method. The research dataset was sourced from Twitter, containing complaints regarding service disruptions of SIAM UB. The classification results revealed an accuracy level of 86% [17]

In contrast to previous research, the study conducted by Yoga et al. centers on the analysis of student reviews regarding faculty performance in both mandatory and elective courses. The research data was collected through a survey conducted at SIAM UB, yielding a total of 3,805 reviews. The Random Forest algorithm was employed in this study, achieving an accuracy rate of 90%, precision of 99%, recall of 96%, and an F1-Score of 97% [18].

From the literature review previously discussed, it can be concluded that the Naïve Bayes method is widely utilized in sentiment analysis of student feedback on academic information systems. The accuracy results vary depending on additional methods such as cross-validation or feature selection. Although alternative techniques like Random Forest and K-Nearest Neighbors have demonstrated superior accuracy in some research, Naïve Bayes remains a suitable choice for this research due to its computational efficiency, ease of implementation, and consistent performance on smaller datasets such as the one used in this study. These studies contribute to a better understanding of student

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perceptions regarding academic services and serve as a foundation for the development of more accurate sentiment analysis models in the future.

3 Research Method

This research employs a structured approach comprising five key phases. It commences with data crawling to gather pertinent textual information, which is then subjected to data labeling to separate the dataset into training and testing segments. The third phase involves preprocessing, where the text is refined and standardized to enhance uniformity. Following this, sentiment analysis is performed utilizing the Naïve Bayes classification technique. Finally, the results are illustrated through a word cloud to emphasize frequently used terms. The complete workflow is depicted in Figure 1.

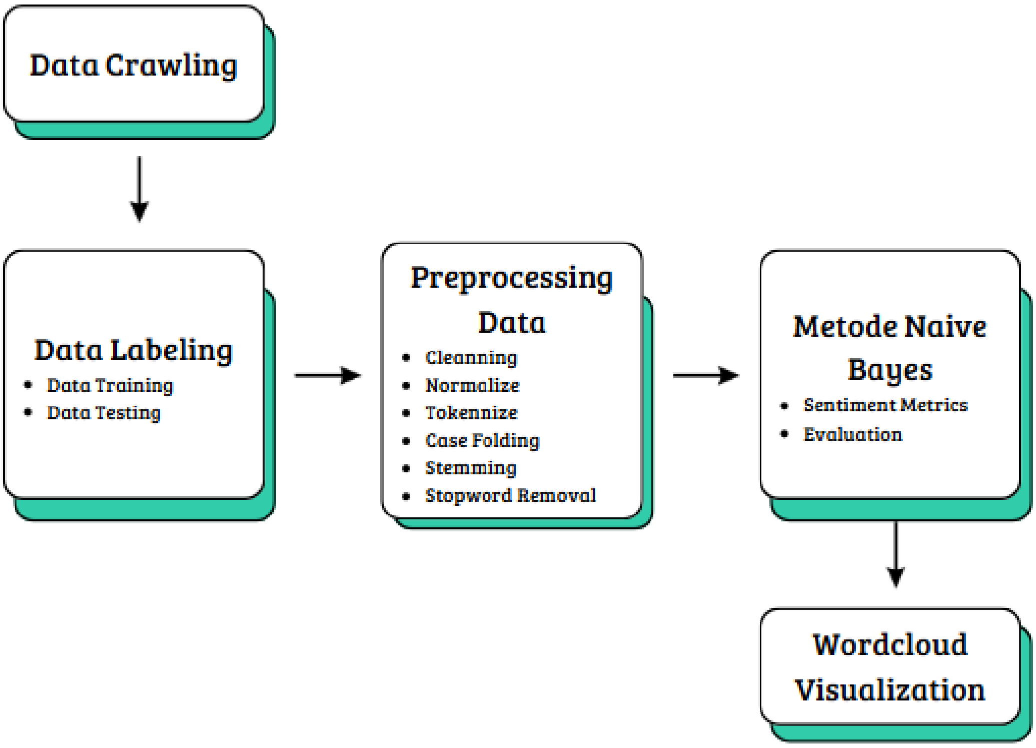

Figure 1. Research methodology

Each phase is essential for generating dependable sentiment analysis outcomes, starting from the initial data acquisition to the ultimate presentation of findings.

3.1 Data Crawling

The study implements the Naive Bayes Classifier method utilizing Google Colab, based on the collected student comment review data. The Naive Bayes algorithm will predict outcomes by leveraging the initial probabilities of each label derived from the training set, along with the contribution of each feature [19]. The dataset employed in this research consists of student reviews regarding the Academic Information System of Sriwijaya University, gathered from social media platform Twitter through the use of an Application Programming Interface (API) [20]. The term "simak unsri" was used to retrieve relevant discussions, thereby ensuring that the dataset accurately represents user experiences with the system. Since Twitter is a popular platform where students often share their opinions on academic services, this dataset offers significant insights into user sentiment.

3.2 Labeling Data

The collected data is categorized into two segments, with 70% designated as labeled training data and 30% as unlabeled testing data, a method known as the hold-out technique [21]. The training data is manually labeled with positive and negative sentiments, followed by a pre-processing phase. Due to the irregular structure of text data, several steps are necessary to prepare the text for a more structured format [22]. This division aims to enable the model to learn patterns from the training data and then be tested on unseen data to evaluate its performance [23]

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3.3 Pre – processing Data

The data pre-processing stage aims to ensure that the data to be used in the analytical model or machine learning is clean, relevant, and in the right format. Cleansing data use eliminating irrelevant components, empty values, or noise, including emoticons, hashtags, usernames, and URLs [24]. Normalization seeks to enhance consistency in text analysis by converting misspelled words, abbreviations, or slang into their standard forms, thereby ensuring that the analysis results are more valid and reliable [25]

Tokenizing uses spaces to divide the comment text into separate words [26] Case folding involves converting all characters to lowercase to avoid confusion and interference with the results [27]. Stemming reduces words to their root forms to improve the consistency of the analysis [28]. Stopword removal entails eliminating frequently occurring words that do not contribute to the analysis, such as 'di', 'yang', 'ke', 'dari', and others [29]

3.4 Naïve Bayes Method

Based on user sentiment, which is converted into a numerical format using Term Frequency-Inverse Document Frequency (TF-IDF) [30] . This allows the algorithm to evaluate the significance of each word. The simplicity, computational efficiency, and resilience of Naive Bayes Classifier (NBC) against irrelevant features and missing data ensure its optimal performance, even in resource-constrained environments [31]. In this study, a multinational approach to Naive Bayes is employed with the equation for sentiment classification expressed in equation (1).

$$P(H|X) = \frac{P(H|X)\ P(H)}{P(X)} \tag{1}$$

The effectiveness of the Naïve Bayes classifier is influenced by the representation of features and the presence of class imbalance. Inadequate feature selection can lead to decreased accuracy, whereas an imbalanced dataset may introduce bias favoring the more prevalent class. It is essential to tackle these issues to enhance sentiment classification.

3.5 Confusion Matrix

Confusion Matrix is used to evaluate the performance of the model by measuring the number of correct and incorrect predictions in each class. Using metrics such as precision, recall, and F1-score, we can assess the effectiveness of the model in classifying sentiments [32]. To evaluate the model, this matrix comprises four variables or components that is TP (True Positive) and TN (True Negative) variables indicate the correct predictions made by the model overall, while the FP (False Positive) and FN variables represent the total number of incorrect predictions generated by the model [33]. An effective model should ideally achieve a high number of true positives (TP) and true negatives (TN) while reducing false positives (FP) and false negatives (FN). A low precision in identifying positive sentiment may suggest an increased occurrence of FP cases, where neutral or negative sentiments are incorrectly categorized as positive. This issue may arise from the overlap of linguistic characteristics among sentiment categories or a lack of adequate distinguishing features. Assessing these metrics is essential for enhancing the model and increasing classification accuracy.

Table 1 Confusion matrix

	Predict Positive	Predict Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	False Negative (FN)

3.6 Word cloud

Word cloud like visual representation of frequently occurring or dominant words associated with a theme[34].Word cloud visualization is expected to provide better insight and understanding of the interpretation of a particular word or theme.

4 Results and Analysis

This research utilizes data sourced from Twitter by leveraging the Twitter API, which facilitates automated data collection. The data collection period spans from March 2023 to August 2024, focusing on the keyword "simak unsri," resulting in a total of 104 sentiment instances. This ensures

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that the captured opinions genuinely reflect student sentiments toward the system in a natural online environment. While the dataset size may be relatively small for sentiment analysis, it effectively captures recurring issues and concerns raised by students. Additionally, since Twitter is an open platform where students actively share their opinions, even a limited dataset can provide meaningful insights. Future research can expand the dataset by incorporating more keywords or sourcing data from other social media platforms to enhance coverage and model performance.

Table 2. Labeling data

Label	Total
Positive	26
Negative	38
Total Training	64

Following the data crawling phase, manual labeling was conducted to prepare the data for training, categorizing the sentiments into two classes: positive and negative. Tweets are categorized as positive when they convey appreciation, praise, or satisfaction toward the system. In contrast, tweets that express complaints, criticism, or dissatisfaction are categorized as negative. The results are presented in Table 2. To evaluate the accuracy of the Naïve Bayes model, the labeled dataset was divided into 70 percent training data, which consists of 64 tweets, and 30 percent testing data, which consists of 27 tweets. Unlabeled data were set to null and used in the testing phase. Labeling was conducted prior to the pre-processing stage to prevent sentiment confusion, as some words may be removed during the stopword phase. As shown in Table 3, text pre-processing stage includes several steps, such as cleaning, standard word normalization, tokenization, case folding, stemming, and stopword removal. After the cleaning process, the resulting clean data, the final dataset consisted of 91 labeled tweets, which were then used in the model training and evaluation process.

Table 3. Example preprocessing step

Preprocessing	**Output**
Cleaning	Simak unsri kenapa terjadi kesalahan server terus tiap klik krs
Normalize	Simak unsri kenapa terjadi kesalahan server terus setiap klik krs
Tokenize	['Simak', 'unsri', 'kenapa', 'terjadi', 'kesalahan', 'server', 'terus', 'setiap', 'klik', 'krs']
Case folding	['simak', 'unsri', 'kenapa', 'terjadi', 'kesalahan', 'server', 'terus', 'setiap', 'klik', 'krs']
Stemming	['simak', 'unsri', 'kenapa', 'jadi', 'salah', 'server', 'terus', 'tiap', 'klik', 'krs']
Stopword	['simak', 'unsri', 'salah', 'server', 'klik', 'krs']

The cleaned data will be processed using the Naïve Bayes modeling approach. The training and testing datasets will be divided using a data split method in Python. Following this division, the vectorization stage will convert the text into a numerical format suitable for processing by the Naïve Bayes model. In this study, the method employed is Term Frequency - Inverse Document Frequency (TF-IDF). This technique not only transforms text into numerical values but also assigns weights to each word based on its frequency in a single document relative to the entire document set. Consequently, words that are more significant for sentiment determination will carry higher weights, while common words that appear frequently across many documents will have lower weights. The output from this vectorization process will serve as the primary input for training the model, which will subsequently be utilized to classify sentiment in the test data.

Once the model has been trained using the training data, the next step is to evaluate its performance with a test dataset that has not been previously utilized. The model will be assessed to determine its ability to recognize the learned patterns and apply them to different texts. The predictions from this model yielded 27 outcomes, with 25 classified as negative sentiment and the remaining 2 as positive sentiment. The results from the Naïve Bayes classifier can be employed to assess the model's effectiveness in classifying user sentiment towards SIMAK, utilizing a confusion matrix. This matrix will provide a visual representation of the model's

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classification performance, including calculations for accuracy, precision, recall, and F1-score, formatted in a contingency table as shown in Table 4.

Table 4. The performance of confusion matrix

	Precision	**Recall**	**F1-Score**	**Support**
Negative	0.63	1.00	0.77	12
Positive	1.00	0.12	0.22	8
Accuracy			0.65	20
Macro avg	0.82	0.56	0.50	20
Weighted avg	0.78	0.65	0.55	20

The table indicates that the model excels in identifying negative classes, attaining a recall of 1.00 and an F1-score of 0.77. In contrast, its performance in recognizing the positive class is still low, demonstrated by a notably low recall of 0.12 and an F1-score of 0.22. The diminished precision in the positive class highlights a disparity between accuracy and completeness in its predictions, as the model frequently produces a significant number of false positives for the positive category.

The notable difference between positive and negative classes may arise from an imbalanced data distribution, where instances of negative sentiment outnumber those of positive sentiment. This imbalance leads to the model being more adept at identifying patterns associated with the negative class, resulting in less than optimal performance in detecting positive sentiments. The low macro F1-score of 0.50 reflects that the performance of the overall classification is still not optimal, especially in classifying positive sentiments. To address this issue, a more strategic approach is needed, such as data balancing using methods like oversampling or the potential implementation of more sophisticated classification techniques..

In previous research, comparisons have been made between Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression in the context of sentiment analysis. According to a study conducted by Imam Syahrohim et al. [35], Logistic Regression achieved the highest accuracy at 84.39%, followed by SVM at 82.08%, while Naïve Bayes recorded an accuracy of only 73.99%. These findings indicate that SVM and Logistic Regression are more effective for sentiment classification, as they can identify more intricate patterns than the simpler probability-based Naïve Bayes method. Consequently, future studies should explore the use of SVM or Logistic Regression, along with other methodologies, to enhance the analysis of student opinions regarding SIMAK UNSRI.

To further understand student sentiment, a word cloud visualization was employed to analyze frequently occurring words in user reviews. This technique complements the previous classification analysis by providing a broader view of common themes and concerns expressed by students. The size of each word represents its frequency in the dataset, making it easier to identify the key issues that students frequently discuss. SIMAK. By highlighting the most relevant keywords, the word cloud offers valuable insights for sentiment analysis, allowing stakeholders to evaluate the system more effectively and implement improvements based on user feedback.

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Figure 2. Word cloud data

The analysis indicates that several prominent keywords are linked to the use of SIMAK UNSRI, particularly concerning technical difficulties. Terms such as "SIMAK," "UNSRI," "tidak," "baru," "error," and "nilai" are displayed in larger fonts, signifying frequent mentions as illustrated in Figure 2. The occurrence of "tidak" and "error" points to ongoing complaints or system issues, while "baru" may indicate discussions about system updates. These insights underscore critical areas for enhancement, ensuring that necessary upgrades are in line with user concerns and expectations.

Despite these concerns, the word cloud also reveals instances of positive feedback. As illustrated in the Figure 3, words such as "thank you" and "alhamdulillah" stand out, reflecting that many students appreciate SIMAK UNSRI, especially regarding new features and access to grades. These findings suggest that certain elements have successfully met user needs and could represent strengths to be maintained. Nevertheless, there are still indications that the system is not yet fully optimized. Further improvements are necessary to enhance the overall user experience.

Figure 3. Word cloud label positive

On the other hand, the word cloud representing negative sentiment reviews, as illustrated in the Figure 4, highlights the terms that frequently appear in student complaints regarding the system. Words such as "error" and "lag" are prominently sized, indicating the primary issues that are often raised, including system errors, access difficulties, slow loading times, and problems with course registration or grade checking. These complaints underscore the necessity for enhancing system stability, improving access speed, and refining key features to ensure they are more responsive and user-friendly.

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Figure 4. Word cloud label negative

The word cloud emphasizes the key issues encountered by users, providing essential insights for enhancing the system. By analyzing frequently mentioned concerns, decision-makers can prioritize fixes that align with student needs. While there are some positive remarks, the predominant feedback consists of complaints about the system, especially concerning slow loading times, errors when using features, and obstacles in course registration and grade access. To enhance user experience, improvements should concentrate on boosting server stability and optimizing overall system performance. Furthermore, future studies could investigate different visualization methods, such as topic modeling or network analysis, to improve sentiment analysis and obtain more profound insights.

5 Conclusion

The Naïve Bayes model achieved 65% accuracy in identifying student sentiment toward SIMAK, performing better on negative feedback but struggling to recognize positive sentiment due to its limited presence in the dataset. The model exhibits a perfect recall rate of 100% but suffers from low precision at 12.5% for positive sentiment, leading to a modest F1-score of 22.2%. This suggests a tendency to incorrectly classify non-positive feedback as positive. The findings imply that students' expressions of satisfaction may be less pronounced or inadequately represented in the dataset, complicating their detection. Wordcloud analysis corroborates this, revealing that the majority of feedback focuses on problems such as slow system response times, access issues, and challenges in completing study plans and checking grades. These findings suggest that system improvements focusing on reliability, accessibility, and responsiveness are essential. To enhance classification accuracy, particularly in recognizing positive sentiment, future research should consider alternative methodologies such as Support Vector Machines, Random Forest, Logistic Regression, or advanced deep learning techniques like LSTM. Additionally, integrating data from various platforms could provide a more comprehensive understanding. This study contributes to sentiment analysis in educational technology by revealing how system limitations affect user sentiment and demonstrating the challenges of applying simple models in imbalanced academic data contexts.

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