Proceedings ASTRAtech International Conference
Vol. 1 October 2024, 68-74
https://doi.org/10.52453/aic.v1iOctober.461

Design sentiment classification in educational ai platforms: a case study of uknow.ai using svm

Danang Timotius Victory*, Muhammad Pramudya Miftah

Software Engineering Technology Department, Politeknik Atra, Jakarta, Indonesia

* Corresponding author: timotius.victory@polytechnic.astra.ac.id

Abstract

This paper presents a sentiment analysis of user reviews on the Uknow.AI platform, an AI-powered educational tool aimed at assisting students in solving mathematical problems through image recognition. The study utilized a Support Vector Machine (SVM) model to classify user reviews into positive, negative, and neutral sentiments. Data was collected from user reviews on platforms like Google Play, followed by pre-processing steps including tokenization and Term Frequency-Inverse Document Frequency (TF-IDF) for feature extraction. The SVM model was evaluated based on performance metrics such as accuracy, precision, recall, and F1-score. The model achieved an accuracy of 93.42% with a recall of 99.70%, indicating robust performance in sentiment classification. Word cloud visualizations also highlighted dominant positive terms like "bagus" (good) and "membantu" (helpful), emphasizing the overall satisfaction with Uknow.AI's functionality. The study found that 92.6% of the reviews were positive, reflecting the tool's effectiveness in enhancing student learning. Future research can focus on further improving user experience by addressing any shortcomings.

Keywords: machine learning, sentiment analysis, support vector machine

1. Introduction

Uknow.AI is an AI-driven educational platform designed to assist students, particularly in subjects like mathematics. Originally launched as CheckMath in 2019 ((Study, 2019), the platform focused on providing step-by-step solutions to math problems through advanced image recognition technology. Users could take a photo of a math problem, and the system would offer a detailed, step-by-step solution. This feature quickly made it a favored tool among students seeking reliable homework assistance. Over time, Uknow.AI expanded its offerings beyond mathematics, evolving into a comprehensive educational support system.

With advancements in artificial intelligence, Uknow.AI integrated models like ChatGPT, enabling it to extend its services to subjects such as physics and chemistry. By providing instant explanations across various academic fields, Uknow.AI serves as a versatile learning companion that not only helps students solve specific problems but also deepens their understanding of underlying concepts. This capability aligns with broader trends in the education technology (EdTech) sector, where AI is increasingly utilized to personalize and enhance the learning experience.

A standout feature of Uknow.AI is its 24/7 accessibility, allowing students to seek help whenever needed. This on-demand support is particularly valuable for those facing tight deadlines or needing extra assistance with challenging topics outside traditional study hours. Uknow.AI acts as a personalized tutor, offering instant feedback and explanations that can significantly enrich the learning process.

Developed by Study Evolution EdTech Pte. Ltd. (Uknow.AI, Instant Homework Helper, 2024), Uknow.AI continually expands its capabilities by integrating new question types, refining AI models, and updating features. Recent enhancements include a smart calculator for complex mathematical operations and interactive exercises to reinforce learning. These updates ensure that Uknow.AI remains effective and relevant in the fast-evolving landscape of educational technology.

Currently, Uknow.AI boasts over 5 million downloads worldwide, with more than 90,000 reviews on platforms Google Play. This success highlights the increasing demand for AI-powered educational tools among students seeking efficient and accessible academic support. The platform's ability to deliver accurate solutions to complex problems, especially in mathematics, physics, and chemistry, combined with its user-friendly interface and improving AI capabilities, establishes Uknow.AI as a trusted resource for students and educators alike. Furthermore, the rise of Uknow.AI underscores the growing influence of artificial intelligence in education, bridging gaps in understanding and enabling students to become more independent learners.

As Uknow.AI's popularity continues to rise, understanding user experience becomes increasingly crucial for its ongoing development. With millions of users relying on the platform, it is essential to gather insights into user satisfaction and concerns to maintain high service levels. One effective method to achieve this is through sentiment analysis, which utilizes natural language processing (NLP) to systematically evaluate user sentiments regarding the application (Goniwada, 2023). By categorizing reviews into positive, negative, or neutral sentiments, Uknow.AI's team can effectively pinpoint areas that require attention and improvement. This approach not only enhances the platform's responsiveness to user feedback but also drives its continuous evolution, ensuring that Uknow.AI remains a valuable educational tool for its users.

This study aims to analyze user sentiment through the implementation of machine learning models, particularly the Support Vector Machine (SVM) (Dinar Ajeng Kristiyanti et al., 2023; Dea Safryda Putri et al., 2023). SVM is particularly adept at handling high-dimensional data, enabling efficient classification of reviews into sentiment categories. By leveraging sentiment analysis, Uknow.AI can enhance its understanding of user feedback, guiding future developments and improving overall user satisfaction.

2. Methodology

The sentiment analysis process follows a systematic sequence, as illustrated in Figure 1. First, Data Collection involves gathering 10,000 user reviews from platforms like the Google Play Store. This is followed by Data Pre-Processing, where the raw text is cleaned and prepared for analysis. Next, the data undergoes Training, during which a machine learning model is developed to recognize sentiment patterns. This is followed by Evaluation, where the model's performance is assessed using metrics such as accuracy and precision. Finally, the sentiment analysis classifies the reviews into positive, negative, or neutral sentiments. The following can be seen in Figure 1.

Figure 1. Sentiment analysis process

This structured approach establishes a strong foundation for the analysis. Subsequently, during the Data Pre-Processing stage, the raw text, as illustrated in Figure 2, is cleansed and prepared for further examination. In this study, the dataset consists of 10,000 reviews, filtered based on their star ratings. Reviews with a rating higher than 3 are categorized as positive (1), while those with a rating lower than 3 are categorized as negative (0). Neutral reviews, with a 3-star rating, are excluded from the analysis to focus solely on clear sentiment distinctions. This filtering enhances the classification accuracy by emphasizing the contrast between positive and negative sentiments. This involves deconstructing the text into smaller components through tokenization, ensuring uniformity by converting all characters to lowercase, and eliminating stop words—common terms that lack significant meaning in sentiment analysis. (Jin et al., 2023;Kim et al.,2022). The following can be seen in Figure 2.

	content	score	thumbsUpCount	\
0	Aplikasi nya ga sesuai apa yang di bayangin, k...	1	9	
1	sangat berguna tidak cuma buat matematika,tapi...	5	724	
2	Membantu jika ada pr yang sulit dan membantu s...	5	112	
3	Apk masih dalam pengembangan, mungkin jika sud...	3	6	
4	aku nulis 4 malah 9 muluu, kesel lama lama! ka...	5	1049	
...	...	...	...	
9995	Indonesia	1	0	
9996	bagus	5	0	
9997	mantap	5	0	
9998	mantap	5	0	
9999	keren	5	0	

Figure 2. Raw data

The data that has undergone pre-processing is illustrated in Figure 3. Following this step, the pre-processed text is converted into numerical data through feature extraction, a critical component of the Training process. Techniques such as Bag of Words (BoW) (Wankhade et al., 2022) and Term Frequency-Inverse Document Frequency (TF-IDF) (Liu et al., 2022) are commonly utilized in this phase. While BoW treats the text as a collection of words without regard for their order, TF-IDF assigns significance to words based on their frequency within the dataset, thus highlighting the importance of certain terms in the context of sentiment analysis (Ahuja et al., 2019). The following can be seen in Figure 3.

	sentence	label
0	Aplikasi nya ga sesuai apa yang di bayangin, k...	0
1	sangat berguna tidak cuma buat matematika,tapi...	1
2	Membantu jika ada pr yang sulit dan membantu s...	1
3	aku nulis 4 malah 9 muluu, kesel lama lama! ka...	1
4	Aplikasi ini sangat berguna,saat kesulitan men...	1
...	...	...
9673	Indonesia	0
9674	bagus	1
9675	mantap	1
9676	mantap	1
9677	keren	1

Figure 3. Data after pre-processing

Among various approaches, Support Vector Machines (SVM) have emerged as a powerful and effective method for sentiment analysis. This supervised learning algorithm excels in classification tasks by identifying a hyperplane that best separates the data into distinct classes—positive, negative, or neutral—in a high-dimensional space. SVM's capability to perform well in high-dimensional settings makes it ideal for text classification, while its robustness against overfitting offers a significant advantage in complex data environments (Zainuddin & Selamat, 2014;Mukarramah et al., 2021).

After selecting the SVM model, the next crucial step is to divide the dataset into training and testing subsets. The training subset is employed to train the SVM model, while the testing subset is used to evaluate its performance. Techniques such as cross-validation can further enhance the reliability of the model by ensuring it generalizes well to unseen data. Once trained, the model can classify new, unseen reviews based on the established decision boundary, providing insights into the sentiment expressed in the review—whether positive, negative, or neutral. Various evaluation metrics, including accuracy, precision, recall, and the F1 score, are utilized to assess the performance of the sentiment analysis model (Maitama et al., 2020; Khan et al., 2023;Maulana Abrari & Abdulloh, 2024).

3. Result and Discussion

The sentiment analysis of Uknow.ai user reviews using a Support Vector Machine (SVM) model provides a detailed understanding of the model's classification capabilities, as reflected in the confusion matrix. The matrix summarizes the performance of the SVM model in classifying user sentiments into positive and negative categories. This analysis is critical for determining the effectiveness of the model in distinguishing between different types of user feedback, which can offer valuable insights into customer satisfaction with the Uknow.ai platform. From the confusion matrix, the SVM model successfully classified 2672 instances of positive reviews correctly (True Positives). This indicates that the model has a strong ability to identify positive sentiments in user reviews. Additionally, the SVM model accurately predicted 41 negative reviews (True Negatives). Although the number of true negatives is significantly lower than that of true positives, this still indicates that the model can identify a small portion of negative reviews correctly. However, the model also encountered challenges, particularly in the misclassification of negative reviews as positive. The confusion matrix shows 183 false positives, where the SVM model incorrectly predicted negative reviews as positive. The following can be seen in Figure 4.

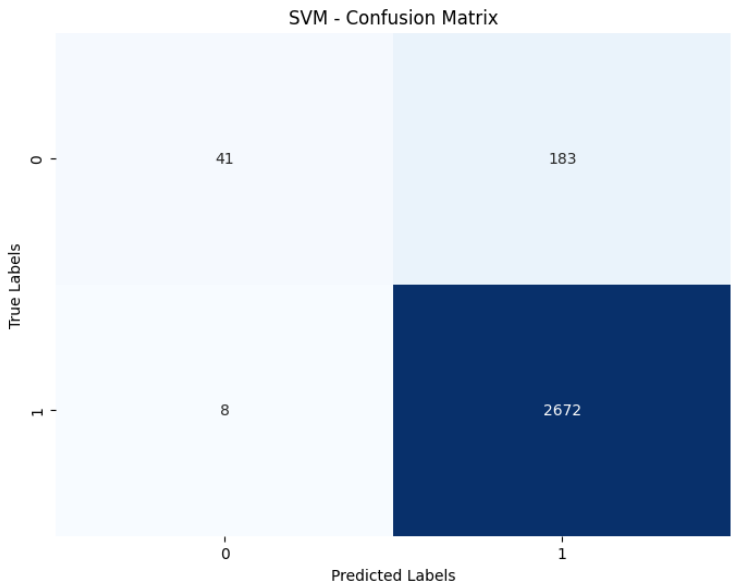

Figure 4. Confusion matrix SVM

Furthermore, the confusion matrix reveals 8 false negatives, where the SVM model misclassified positive reviews as negative. Although this number is relatively small compared to the total number of reviews, it still represents a limitation in the model's ability to accurately classify all positive reviews.

Overall, the SVM model demonstrates a strong ability to accurately identify positive sentiments, as reflected in the confusion matrix. However, there is potential to further enhance its performance in distinguishing between positive and negative reviews, particularly in cases where the sentiment might be less clear. The presence of 183 instances of reviews predicted as positive, which were actually negative, suggests an opportunity to refine the model's ability to recognize more nuanced feedback.

By focusing on these areas of refinement, the model's overall performance can be further enhanced, contributing to a more precise sentiment analysis. This potential for improvement is also reflected in the key evaluation metrics, which offer deeper insights into the model's effectiveness. With an accuracy of 93.42%, the SVM model demonstrates a high level of reliability in classifying the sentiments of user reviews. This metric suggests that the model correctly predicts the sentiment in the vast majority of cases. The recall of 99.70% indicates that the model is highly effective in identifying positive reviews, successfully capturing nearly all instances of positive sentiment. This strong recall performance reflects the model's robustness in recognizing positive feedback, ensuring that almost no positive reviews are missed. On the other hand, precision stands at 93.59%, suggesting that while the model excels at identifying most positive sentiments, a small portion of negative reviews is incorrectly classified as positive. This is consistent with the earlier observation of false positives, where some negative sentiments are misinterpreted as positive. Finally, the F1-score of 96.55% balances the model's precision and recall, demonstrating a strong overall performance in handling user reviews. The F1-score underscores the model's ability to maintain a high level of accuracy while minimizing the trade-off between correctly identifying positive sentiments and avoiding the misclassification of negative ones. The following can be seen in Figure 5.

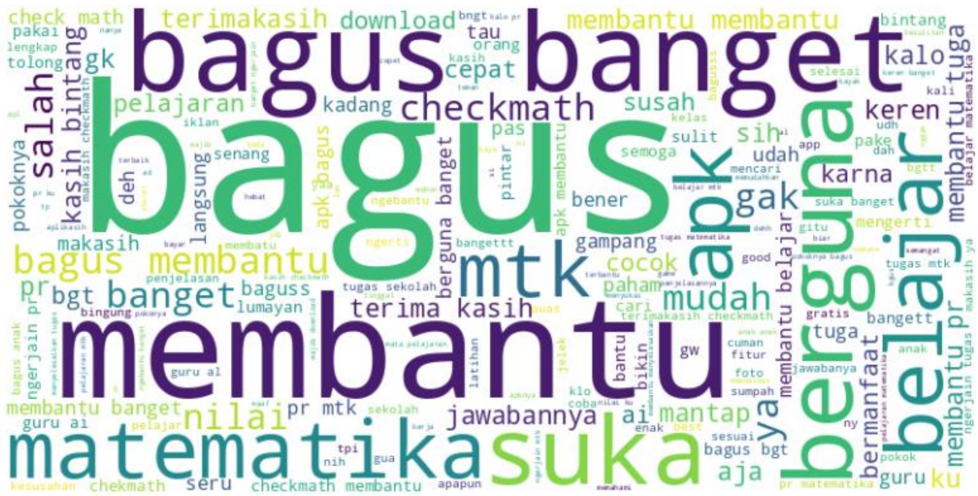

Figure 5. WordCloud for uknow.ai

The word cloud visualization provides an insightful overview of the most frequently used words in user reviews for Uknow.ai, reflecting key sentiments and themes in user feedback. The prominence of words such as "bagus" (good), "membantu" (helpful), "banget" (very), and "belajar" (learning) indicates a generally positive user experience. These words suggest that users find the app helpful, particularly in the context of learning, likely referring to its educational features. The word "matematika" (mathematics) also appears frequently, implying that the app is widely used for assisting with math-related tasks, which could be a core function of the app.

The presence of highly positive words like "suka" (like), "terimakasih" (thank you), and "bagus banget" (very good) further reinforces the idea that users are generally satisfied with the app's performance and usefulness. These positive sentiments highlight the app's value in helping users, particularly students, improve their skills or understanding of various subjects.

On the other hand, some neutral or potentially negative words such as "susah" (difficult) and "salah" (wrong) also appear, although they are significantly smaller in size. This suggests that while most users have a favorable opinion of Uknow.ai, there may still be occasional challenges or difficulties, such as incorrect answers or certain aspects of the app being hard to use. Overall, the word cloud indicates that the majority of users express positive sentiments about Uknow.ai, particularly in its educational value, with only a few mentions of challenges or issues.

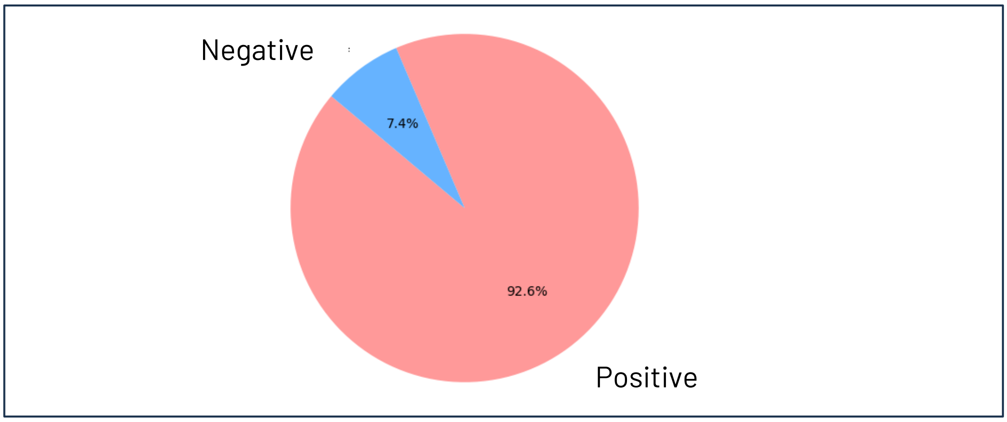

Figure 6. Sentiment analysis result

The sentiment analysis of Uknow.ai user reviews, as depicted in the pie chart as shown in figure 6, reveals a dominant trend of positive sentiment, comprising 92.6% of the total reviews. This overwhelming proportion of positive feedback suggests that most users have had favorable experiences with the application, aligning with the word cloud analysis that highlighted terms such as "bagus," "membantu," and "suka," which emphasize the app's usefulness and satisfaction among users.

The 7.4% of reviews reflecting negative sentiment is relatively small, indicating that only a minority of users have encountered challenges or expressed dissatisfaction. This could relate to issues such as difficulty in using certain features, incorrect answers, or unmet expectations. Although the negative feedback is minimal, it is still important to analyze these reviews in more detail to identify specific areas of improvement.

Overall, the sentiment distribution strongly underscores Uknow.ai's success in delivering a positive user experience. The high percentage of positive reviews reflects user satisfaction with the app's functionality, particularly its educational aspects, such as helping with mathematics. However, the small portion of negative feedback serves as a valuable reminder that continuous improvements could further enhance user satisfaction and address any lingering issues.

4. Conclusion

In summary, the analysis of Uknow.ai through various methodologies, including word cloud visualizations, confusion matrices, and evaluation metrics, reveals a comprehensive understanding of user sentiment and application performance. The word cloud highlights the prevalence of positive terms such as "bagus" and "membantu," showcasing user satisfaction and the app's effectiveness in educational contexts, particularly in mathematics.

The confusion matrix provides a quantitative measure of the model's performance, indicating a high accuracy rate of 93.42%. The evaluation metrics further reinforce this by demonstrating a recall of 99.70%, precision of 93.59%, and an F1-score of 96.55%. These metrics illustrate the model's ability to accurately identify sentiments while also highlighting a small percentage of false positives that suggest areas for refinement.

The insights gained from this multifaceted analysis are critical for guiding the future development of Uknow.ai. Addressing the minor negative sentiment and enhancing model precision will not only improve user experience but also ensure the application continues to meet the evolving needs of its user base. Therefore, this research underscores the significance of utilizing user feedback and performance metrics in the continuous improvement of educational technologies, ultimately contributing to better learning outcomes.

References

Dea Safryda Putri, Sulistiyowati, N., & A. Voutama. (2023). Analisis Sentimen dan Pemodelan Ulasan Aplikasi AdaKami Menggunakan Algoritma SVM dan KNN. Journal Sensi.

Dinar Ajeng Kristiyanti, Dwi Andini Putri, Indrayuni, E., Acmad Nurhadi, & Akhmad Hairul Umam. (2023). Twitter sentiment analysis using support vector machine and deep learning model in e-learning implementation during the Covid-19 outbreak. AIP Conference Proceedings. https://doi.org/10.1063/5.0128685

Ahuja, R., Chug, A., Kohli, S., Gupta, S., & Ahuja, P. (2019). The Impact of Features Extraction on the Sentiment Analysis. Procedia Computer Science, 152, 341–348. https://doi.org/10.1016/j.procs.2019.05.008

Goniwada, S. R. (2023). Sentiment Analysis. Apress EBooks, 165–184. https://doi.org/10.1007/978-1-4842-9496-3_6

Jin, Y., Cheng, K., Wang, X., & Cai, L. (2023). A Review of Text Sentiment Analysis Methods and Applications. Frontiers in Business, Economics and Management, 10(1), 58–64. https://doi.org/10.54097/fbem.v10i1.10171

Khan, J., Ahmad, N., Khalid, S., Ali, F., & Lee, Y. (2023). Sentiment and Context-Aware Hybrid DNN With Attention for Text Sentiment Classification. IEEE Access, 11, 28162–28179. https://doi.org/10.1109/access.2023.3259107

Kim, C.-G., Hwang, Y.-J., & Kamyod, C. (2022). A Study of Profanity Effect in Sentiment Analysis on Natural Language Processing Using ANN. Journal of Web Engineering. https://doi.org/10.13052/jwe1540-9589.2139

Liu, H., Chen, X., & Liu, X. (2022). A Study of the Application of Weight Distributing Method Combining Sentiment Dictionary and TF-IDF for Text Sentiment Analysis. IEEE Access, 10, 32280–32289. https://doi.org/10.1109/access.2022.3160172

Maitama, J. Z., Idris, N., Abdi, A., Shuib, L., & Fauzi, R. (2020). A Systematic Review on Implicit and Explicit Aspect Extraction in Sentiment Analysis. IEEE Access, 8, 194166–194191. https://doi.org/10.1109/access.2020.3031217

Maulana Abrari, M. N., & Abdulloh, F. F. (2024). COMPARISON OF MACHINE LEARNING ALGORITHMS FOR SENTIMENT ANALYSIS OF DIGITAL IDENTITY APPLICATION USERS. Jurnal Pilar Nusa Mandiri, 20(2), 146–154. https://doi.org/10.33480/pilar.v20i2.5736

Mukarramah, R., Atmajaya, D., & Ilmawan, L. B. (2021). Performance comparison of support vector machine (SVM) with linear kernel and polynomial kernel for multiclass sentiment analysis on twitter. ILKOM Jurnal Ilmiah, 13(2), 168–174. https://doi.org/10.33096/ilkom.v13i2.851.168-174

Study. (2019, January 29). Uknow. AppAdvice. https://appadvice.com/app/uknow-ai-homework-math-solver/1447618956

Uknow.AI, Instant Homework Helper. (2024). Checkmath.net. https://www.checkmath.net/

Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. Artificial Intelligence Review, 55(55). https://doi.org/10.1007/s10462-022-10144-1

Zainuddin, N., & Selamat, A. (2014). Sentiment analysis using Support Vector Machine. 2014 International Conference on Computer, Communications, and Control Technology (I4CT). https://doi.org/10.1109/i4ct.2014.6914200