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Sentiment Analysis on User Reviews of Snapchat in Indonesia

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Abstract: This research explores the sentiment expressed in Snapchat user reviews within the Indonesian context, leveraging advanced natural language processing techniques and classification models. With a focus on the Indonesian user base, 8,015 reviews from the Google Play Store were analyzed using naive bayes, Support Vector Machines (SVM), and random forest models. The results indicated that the random forest model outperformed others with an 83% accuracy rate, followed by SVM at 81% and naive bayes at 80%. The analysis of frequently mentioned words in positive and negative reviews unveiled key aspects influencing user satisfaction. Positive reviews highlighted terms like 'bagus' (good) and 'suka' (like), while negative reviews often mentioned 'jelek' (bad) and technical issues like 'download.' The study contributes valuable insights for developers to enhance user experience on the Snapchat platform and suggests directions for future research in sentiment analysis of social media reviews.

Keywords: Sentiment Analysis, User Reviews, Naive Bayes, Support Vector Machine, Random Forest, Snapchat, Indonesia

Introduction

Research Background

A small group of Stanford University students created the Snapchat app, which was released in September 2011 and works with both Google Android and Apple iOS smartphones. The Federal Trade Commission (FTC) received a complaint against Snapchat Inc. From the Electronic Privacy Information Center (EPIC) in May 2013. The complaint claimed that the company was deceiving users into thinking that images were instantly deleted from Snapchat servers (McLaughlin, 2024). Snapchat is a social networking site where users may network and exchange content (Glenn, 2018). Snapchat takes pictures with the device's camera and distributes them to other Snapchat users. With the help of the software, the sender can add text or draw on the snapshot and specify how long the receiver can view it before the image vanishes from their device. Messages are limited to one viewing. The receiver has to keep their finger on the touchscreen the entire viewing time, otherwise the snap will vanish (McLaughlin, 2024). Snapchat's global user base has been projected to increase from 493.9 in 2022 to 525.7 million in 2023 (Lebow, 2023).

Problem Identification

In January 2023, there were 167.0 million social media users in Indonesia or 60.4% of the country's entire population. There were 3.55 million users of the Snapchat application in Indonesia alone at the beginning of 2023, making Snapchat the 13th top social media platform in Indonesia alone in early 2023. An unprecedented amount of user-generated material has resulted from social media platforms' growing popularity and online evaluations are an important source of information for prospective users (Kemp, 2023; Sue, 2024). This article proposes to examine the intricacies of sentiment represented in Snapchat user reviews on Indonesians. This research builds upon the work of Evaristus *et al*. (2022) who evaluated the accuracy of three sentiment analysis models: Support Vector Machine (SVM) (94.2%), random forest (93.7%), and naive bayes (92.7%). We aim to extend their work by focusing specifically on sentiment analysis of user reviews for Snapchat in Indonesia. This study will first introduce the problem of understanding user sentiment on social media platforms like Snapchat. We will then discuss the research objectives and methodologies employed in this study. Finally, we will present the sentiment analysis strategy used and analyze the results obtained from our investigation.

App Review and Rating

App store ratings and reviews reflect the popularity of your app as well as user opinions. Reviews and ratings are open-ended comments left by past or present app users that discuss their experiences with developers, whether they like or dislike the app (APPRADAR, 2023). Stakeholders can utilize app reviews and ratings to gain important insights into user satisfaction and to guide future development and modification work Senanu and Ooreofe (2021). App reviews give developers insight into user experiences, requirements, and problems that arise after using the app, enabling them to fix these problems and make improvements (Cheng *et al*., 2021).

Sentiment Analysis

Sentiment analysis is the study of creating tools and computer methods to identify, categorize, and extract views and feelings that people express on blogs, forums, social networks, and other online platforms (Denilson Alves, 2020). Conventional text representation schemes, N-gram models, and machine learning classifiers such as logistic regression, support vector machines, naive bayes, and random forest algorithms are examples of sentiment analysis techniques (Toçoğlu and Onan, 2020).

Naive Bayes

Naive bayes is a machine-learning technique that improves the precision of information and feature extraction from textual materials (Nadia *et al*., 2021). Naive Bayes uses a probabilistic model to classify articles into different groups. The benefit of employing naïve bayes is that it can identify the estimated parameters required for the classification process with only a minimal amount of training data (Evaristus *et al*., 2022).

Support Vector Machines

In machine learning, Support Vector Machines (SVMs) are a class of supervised learning models that are employed for classification and prediction tasks. In the context of sentiment analysis, SVMs can be used to evaluate text data and determine the sentiment or emotion that underlies the text. SVMs are able to forecast a text's sentiment score and categorize text data into many sentiment categories, such as positive, negative, or neutral. SVMs can also be used to combine many information sources, including text, image, and audio data, and to classify text data into distinct subjects or themes in order to provide a more thorough understanding of the sentiment included in the text. SVMs have demonstrated strong performance on benchmark datasets, obtaining high accuracy in tasks involving sentiment classification (Sridhar Mocherla *et al*., 2017).

Random Forest

Random forest is an ensemble learning method used for classification and regression tasks in machine learning (Nfn, 2019). The Random Forest method works by constructing multiple decision trees and combining their predictions to improve the overall accuracy and efficiency of sentiment classification (Yehia, 2023).

Web Scraping

Web scraping is a collection of methods used to automatically extract information from websites, process unstructured data, and store it in organized databases. By examining the content of a website, web scraping tools can efficiently identify the most pertinent advertisements for a generic website (Eloisa and Mirko, 2012).

Confusion Matrix

A confusion matrix is a table that displays the number of accurate and inaccurate guesses for each class, representing the prediction summary in matrix form (Ajay *et al*., 2020). A confusion matrix provides details on the accuracy, precision, recall, and F1-score of a machine learning model, which is useful when assessing the model's performance in sentiment analysis. A confusion matrix is used to evaluate the model's overall performance and identify the classes that the model is confusing with other classes (Ajay *et al*., 2020; Kundu, 2022). Four categories are used to arrange a confusion matrix: False Positives (FP), False Negatives (TN), True Positives (TP), and False Negatives (FN). These categories can be used to compute a number of performance metrics that give a more thorough picture of the model's performance, including accuracy, precision, recall, and F1-score (Narkhede, 2021).

Sastrawi Library

A Python module called Sastrawi can be used to lower errors when converting Indonesian into standard form (stem) Jehezkiel (2020).

NLTK Library

Using third-party libraries for regular expression retrieval, syntax analysis, and graphic rendering, along with unified data standards, the Python-based NLTK library offers extensive and versatile research methodologies for corpus research (Meng and Fanghui, 2021). This article utilizes the NLTK in many categorization model methods.

Scikit-Learn Package

A Python module called Scikit-learn integrates a variety of cutting-edge machine-learning techniques for medium-scale supervised and unsupervised applications (Abraham *et al*., 2014; Pedregosa *et al*., 2011). Scikit-learn offers a common interface for implementing machine learning algorithms together with tools for preparing data, resampling, adjusting evaluation parameters, and searching interfaces for performance optimization (Ekaba, 2019).

Problem Formulation

In this study, we address two fundamental problem formulations in the context of sentiment analysis on user reviews of Snapchat. Firstly, the research aims to discern the predominant opinions of Snapchat users by collecting data from the Google Play Store, specifically focusing on the Indonesian user base. A comprehensive review will unveil whether Snapchat predominantly garners positive or negative reviews, providing crucial insights for subsequent data analysis and discussion. Secondly, this investigation will conduct a comparative sentiment analysis using the naive bayes, SVM, and random forest classification models on Snapchat user reviews. Employing the Sastrawi library, we will assess the sentiments conveyed within user comments and feedback, aiming to identify prevailing positive or negative sentiments, key themes, and sentiments associated with specific aspects of the Snapchat application. By solving these issue formulations, our research hopes to add to the corpus of literature already available on sentiment analysis, illuminating the complex viewpoints of Snapchat users and deepening our comprehension of user sentiment inside the Snapchat network.

Purpose of the Research

This research on sentiment analysis of Snapchat user reviews has a dual purpose. First, it aims to uncover key sentiments among Snapchat users, providing important insight into whether the platform has generally seen positive or negative feedback. This basic understanding is critical for developers and researchers to measure user satisfaction and identify areas for improvement. Second, by leveraging advanced natural language processing techniques and models such as naive bayes, SVM, and random forest, this research seeks to analyze the nuances of sentiment in user reviews, identifying key themes, sentiment associated with certain features, and potential changes over time to time. By achieving these goals, this research not only contributes to the academic sentiment analysis literature but also offers actionable insights for Snapchat developers to improve the platform based on user preferences, ultimately contributing to a richer user experience.

Benefits of the Research

Sentiment analysis study on Snapchat user reviews offers developers strategic insights that direct focused enhancements to boost user satisfaction and retention. Utilizing sophisticated models such as naive bayes, SVM, and random forest, the research adds to the body of knowledge on sentiment analysis by demonstrating the model's relevance in the setting of social media. A universally applicable understanding is ensured by the emphasis on cultural subtleties. In the end, the research results provide practical suggestions for improving features and resolving issues, resulting in a more satisfying and enjoyable Snapchat user experience.

Problem Scope

The topics covered in this research are limited to the examination of user reviews that were specifically obtained from Snapchat's Indonesian user base on the Google Play Store. The process of gathering data entails using the Google Play Scraper Python module to perform web scraping. Moreover, the data sample that was employed concerns information that was collected from the web crawling method in the last year. Because data older than a year may contain useless information, adding unnecessary noise and risking the data and further analysis, this careful selection of recent samples is meant to guarantee the analysis of current opinions.

Literature Review

Sentiment Analysis of Snapchat User Reviews in Indonesia

The vast amount of user-generated content on social media platforms presents a rich opportunity for businesses and researchers to understand user opinions and experiences (Ambreen *et al*., 2022). Sentiment analysis, a subfield of Natural Language Processing (NLP), plays a crucial role in extracting emotions and attitudes from online text data (Margarita *et al*., 2023). This information is invaluable for gauging user satisfaction, identifying emerging trends, and informing marketing strategies (Grönroos, 2011).

This study focuses on applying sentiment analysis to user reviews of Snapchat, a popular social networking app that has witnessed significant user growth globally. However, concerns regarding user privacy and data retention have sparked questions about user sentiment, particularly within the context of the Snapchat Indonesian user base. By analyzing user reviews from Indonesian users, we aim to gain deeper insights into their satisfaction, identify potential areas for improvement within the Indonesian market, and understand how privacy concerns might be impacting their overall experience.

Sentiment Analysis Techniques

Machine learning algorithms are at the forefront of sentiment analysis, enabling researchers to automatically categorize text data into positive, negative, or neutral sentiment. Two commonly employed algorithms are random forest and Support Vector Machines (SVM).

Random forest: This ensemble learning method builds and combines multiple decision trees, resulting in more accurate predictions (Breiman, 2001).

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Support Vector Machines (SVM): SVM algorithms focus on identifying the optimal separation space within a dataset with different classes, effectively classifying text data into sentiment categories (Cortes and Vapnik, 1995).

The choice of algorithm depends on the specific characteristics of the data and the desired outcome of the analysis.

Related Work

While sentiment analysis has been widely applied to social media platforms, research specifically focused on Indonesian users remains limited.

A relevant study by Park *et al*. (2020) investigated sentiment analysis of social media reviews for mobile apps in Southeast Asia. The study employed Long Short-Term Memory (LSTM) networks, a deep learning technique, to analyze reviews in multiple languages, including Indonesian. Their findings highlight the importance of considering cultural context and language nuances when analyzing sentiment.

Several studies have explored the application of sentiment analysis to social media platforms. Weng *et al*. (2021) investigated user sentiment toward Snapchat using multinomial naive bayes and random forest algorithms to predict user ratings based on reviews. Their findings suggest that both algorithms can be effective in analyzing user sentiment on social media platforms. However, limitations exist in this study, such as the lack of focus on a specific user base (e.g., Indonesian users).

Social media platforms have become a vibrant space for users to share their opinions and experiences. This wealth of data offers valuable insights for businesses and researchers and sentiment analysis techniques are often employed to extract this information (Chen and Lin, 2019). However, for accurate analysis, it's crucial to consider the cultural context of the data to avoid misinterpretations.

A study by Mohammad *et al*. (2017) explores the challenges of sentiment analysis across different cultures. While not directly focused on Indonesia, their research highlights the importance of considering cultural context and language nuances when analyzing social media data. This emphasizes the need for a culturally aware approach when analyzing the reviews of Indonesian users on Snapchat.

Recent advancements in Natural Language Processing (NLP) have introduced pre-trained language models that can be fine-tuned for specific tasks and languages. One such study by Jayadianti *et al*. (2022) investigates the use of Indo BERT, a pre-trained language model specifically designed for the Indonesian language. Their research showcases the potential of leveraging language-specific models for sentiment analysis on Indonesian user reviews. This suggests that utilizing Indo BERT could be beneficial for our analysis. Compared to generic sentiment analysis models, Indo BERT would be better equipped to understand the subtleties and nuances of the Indonesian language, leading to a more accurate analysis of user sentiment.

By critically evaluating existing research and addressing potential limitations, our study aims to contribute to the field of sentiment analysis by focusing on user sentiment toward Snapchat specifically within the context of the Indonesian market.

Materials and Methods

In this study, the research process encompassed several key stages. The initial phase involved gathering data through the utilization of Google Play Scraper for web scraping purposes. Subsequently, the acquired data underwent thorough processing through text preprocessing techniques and the extraction of relevant features. Following these preparatory steps, an in-depth analysis was conducted using sentiment analysis classification methods. The outcomes of the analyses were then subjected to evaluation and comparison, after which the results were visually represented for a comprehensive understanding.

Data Collection

The data acquisition technique employed involves utilizing web scraping through the Python library known as "google-play-scraper." As illustrated in Fig. (1), the gathered data is exported in CSV format, featuring various columns encompassing distinct attributes. However, the primary emphasis in this study centers on the reviews and ratings provided by users specifically for the Snapchat application.

Text Preprocessing

In the sentiment analysis research on user reviews for Snapchat, the data preparation process involves several key steps, as illustrated in Fig. (2). Firstly, relevant reviews are carefully selected to ensure diversity in perspectives. After selection, manual labeling assigns sentiment labels (positive, negative, or neutral) to each review. The data is then normalized to ensure consistent formatting, and case folding is applied to convert all text to lowercase for uniformity. Stop word removal eliminates common, non-informative words such as "the," "and," or "is," enhancing the dataset's clarity. Tokenization breaks down reviews into individual words, while stemming reduces words to their base form. These steps systematically refine the dataset, creating a standardized foundation for training and evaluating sentiment Qanalysis models on Snapchat user reviews.

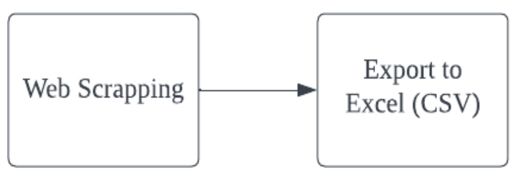

Fig. 1: Data collection method

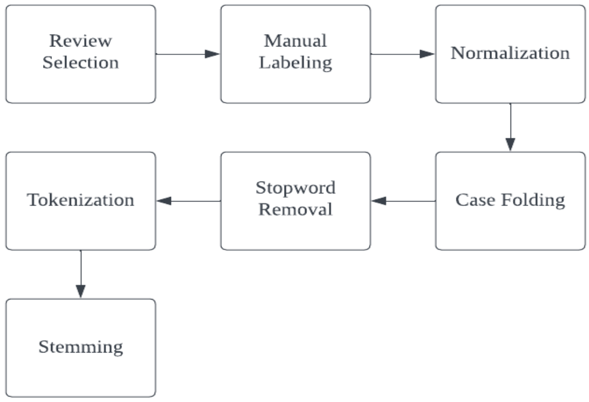

Fig. 2: Text preprocessing method

Features Extraction

In the feature extraction phase for sentiment analysis on Snapchat user reviews, a comprehensive approach is employed. In Fig. (3), the initial process of vectorization is implemented using trigrams and bigrams to capture not only individual words but also meaningful sequences of adjacent words. This step aims to encompass contextual information and enhance the representation of the text data. Subsequently, feature extraction utilizes Term Frequency-Inverse Document Frequency (TF-IDF) to assign weights to terms based on their frequency in each review relative to the entire corpus. TF-IDF emphasizes the importance of terms within individual reviews while also considering their uniqueness across the entire dataset. By combining vectorization with trigrams and bigrams and employing TF-IDF, the feature extraction process results in a nuanced and informative representation of Snapchat user reviews, facilitating the training and evaluation of sentiment analysis models.

Sentiment Analysis Classification

In the classification phase of this research, the dataset consisting of 8,015 entries derived from user reviews on the Google Play Store is divided into training data and testing data using an 80:20 ratio. As shown in Fig. (4), after feature extraction, the data is split into training and testing sets. The sentiment analysis classification techniques utilized in this study encompass Naïve Bayes, Support Vector Machine (SVM), and Random Forest. The training data is used to build models using these methods, while the testing data is employed to evaluate their performance. These methods play a crucial role in categorizing the data into distinct predefined sentiment categories, thereby facilitating a comprehensive analysis of the sentiment expressed in user reviews. Performance calculation and accuracy are assessed using the testing data. The utilization of Naïve Bayes, SVM, and Random Forest classifiers offers diverse approaches to effectively handle the sentiment classification task and enables a thorough evaluation of their respective performances in the context of Snapchat user reviews.

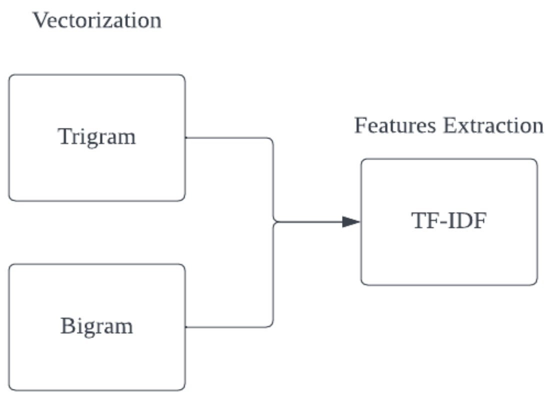

Fig. 3: Features extraction method

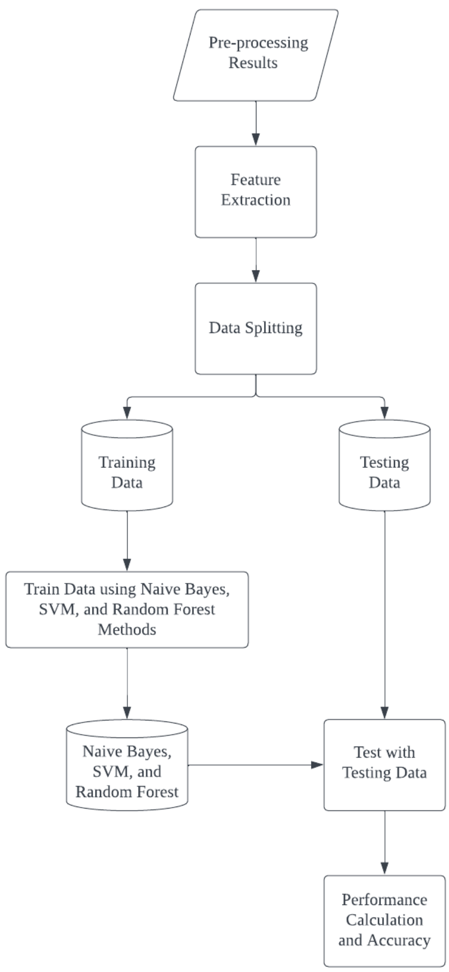

Fig. 4: Sentiment analysis classification method

Evaluation and Comparison

The Confusion Matrix technique is applied to conduct a meticulous assessment of each classification method's performance. This method allows for precise quantification of accuracy in correctly identifying instances across distinct classes, including True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Following the Confusion Matrix analysis, the study delves into additional crucial performance metrics such as Precision, Recall, F1-score, and overall accuracy. This comprehensive approach is essential for establishing a scientifically robust understanding of how each classification method effectively operates within the context of Snapchat user reviews, ensuring a nuanced evaluation of their respective strengths and limitations.

Visualization

In the comparison of sentiment analysis results, the outcomes are presented visually through the utilization of the Matplotlib library in Python, employing a clustered bar chart. Following this visualization, the top ten words associated with positive and negative labels are represented using both a histogram and a word cloud. This visualization approach is designed to provide a comprehensive depiction of the most frequent keywords and their respective frequencies within the positive and negative sentiment categories. By employing both graphical representations and quantitative information, this methodology enhances the interpretability of the sentiment analysis results for user reviews on Snapchat.

Results and Discussion

This research gathered 8,015 user reviews sourced from the Google Play Store and subjected them to text processing procedures to enhance cleanliness and refinement for the purpose of facilitating sentiment analysis. As outlined in Table (1), the dataset was split in an 80:20 ratio, yielding 5,984 samples for training and 1,496 samples for testing. The findings indicate a notable imbalance, with a significantly higher number of positive reviews compared to negative ones. Among the positive testing data, more than 5,500 reviews center on user experiences, while the remaining subset comprises negative reviews highlighting technical issues such as lags or the removal of specific features.

Table 1: Numbers of data split for each label

Label	Data numbers
Training	5984
Testing	1496

Naïve Bayes

The analysis utilized the Multinomial Naive Bayes (NB) model implemented through the Scikit-Learn package and NLTK function to categorize the dataset based on keywords. The assessment of the Naive Bayes technique, employing a confusion matrix, revealed the following outcomes: 84 instances of True Positives (TP), 12 occurrences of False Positives (FP), 1,106 instances of True Negatives (TN), and 294 instances of False Negatives (FN), as outlined in Table (2). This approach yielded an average precision of 81%, an average recall of 80%, an f1-score of 75%, and an average accuracy of 80% for the Naive Bayes technique. The computations for these metrics are detailed in Table (3).

Support Vector Machine

For the construction of a classification model, we employed the Support Vector Machine (SVM) utilizing the Support Vector Classifier (SVC) with a linear kernel from the Python scikit-learn module. After the creation of the classifier, predictions were generated for the Testing data. The assessment of the SVM technique through a confusion matrix revealed outcomes of 149 True Positives (TP), 48 False Positive (FP), 1070 True Negatives (TN), and 229 False Negative (FN), outlined in Table (4). The SVM model utilized in this investigation showcased a performance on par with the Naïve Bayes model, achieving an accuracy of 81,5%. The computation details of the evaluation results can be found in Table (5).

Table 2: Confusion matrix of Naïve Bayes model

	Positive	Negative
Predicted positive	84	2940
Predicted negative	12	1106

Table 3: Classification report of Naïve Bayes model

	Precision-Recall		F1-score	Support
Negative	0.88	0.22	0.300	3780
Positive	0.79	0.99	0.880	1118
Accuracy	0.800	1496		
Macro avg	0.83	0.61	0.620	1496
Weighted avg	0.81	0.80	0.750	1496

Table 4: Confusion matrix of SVM model

	Positive	Negative
Predicted positive	149	2290
Predicted negative	480	1070

Table 5: Classification report of the SVM model

	Precision-Recall	F1-score	Support	
Negative	0.76	0.39	0.52	3780
Positive	0.82	0.96	0.89	1118
Accuracy			0.81	1496
Macro avg	0.79	0.68	0.70	1496
Weighted avg	0.81	0.81	0.79	1496

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Random Forest

The Random Forest (RF) classification method constructs decision trees using randomized data samples. In RF classification, each tree within the forest contributes to the final classification by casting a vote on the class. The assessment of the Random Forest technique, employing a confusion matrix, produced the following outcomes: 175 instances of True Positives (TP), 56 instances of False Positives (FP), 1062 instances of True Negatives (TN), and 203 instances of False Negatives (FN), as outlined in Table (6). In this investigation, a forest consisting of 10 trees was employed and the RF model attained an accuracy of 83%. The detailed calculations for the evaluation results are presented in Table (7).

Sentiment Analysis Classification Comparison

Upon assessing the performance metrics, encompassing precision, recall, f1-score, and accuracy, it was observed that the random forest model exhibited the highest performance score, followed by the SVM model, with the naive bayes model registering the lowest score. Importantly, the disparities in performance scores among the three models were found to be relatively modest. A more granular breakdown of the performance scores for each classification model, presented in Table (8) as percentages (83, 81, and 80%), reveals further insights. To offer a visual representation of the comparative performance, a clustered bar chart using matplotlib was generated. Figure (5) visually depicts that the bar corresponding to the random forest model is marginally higher than the bars associated with the other models, underscoring its superior performance.

Table 6: Confusion matrix of random forest model

	Positive	Negative
Predicted positive	175	203
Predicted negative	56	1062

Table 7: Classification report of random forest model

	Precision	Recall	F1-score	Support
Negative	0.76	0.46	0.57	0378
Positive	0.84	0.95	0.89	1118
Accuracy			0.83	1496
Macro Avg	0.80	0.71	0.73	1496
Weighted Avg	0.82	0.83	0.81	1496

Table 8: Comparison of classification model's result

Model	Precision	Recall	F1-Score	Accuracy
Naïve Bayes	0.811	0.795	0.746	0.795
Support vector machine	0.815	0.807	0.815	0.793
Random forest	0.819	0.827	0.811	0.827

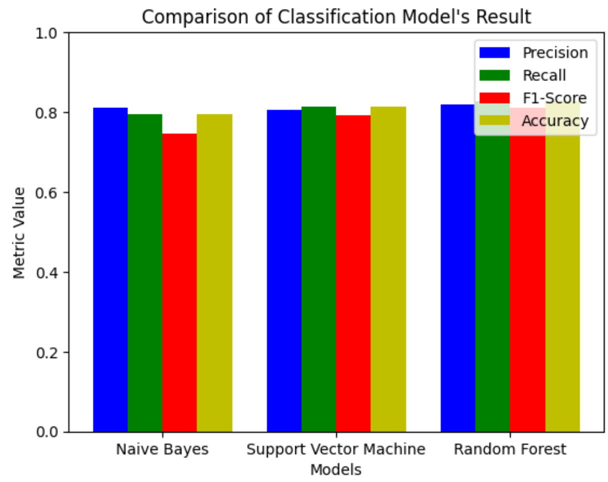

Fig. 5: Classification model performance comparison

Sentiment Analysis Results

Through in-depth analysis and visualization of the Snapchat user review dataset sourced from Google Play Store reviews, this study aims to uncover prevalent topics discussed by users in relation to their positive or negative sentiments regarding the Snapchat application. Following dataset refinement to include only pertinent words for analysis and visualization, a bar chart utilizing matplotlib illustrates the frequency of each word. This bar chart highlights the top ten words commonly used by users in either positive or negative reviews.

In Fig. (6), the 10 most frequently cited words in positive sentiments are showcased. These words encompass 'bagus', 'aplikasi', 'banget', 'sangat', 'aku', 'suka', 'filter', 'snapchat', 'efek' and 'foto'. Notably, 'bagus' emerges as the most frequently used term, appearing over 3,242 times, indicating a prevalent positive sentiment among users who commend the application.

Contrastingly, Fig. (7) illustrates the ten most commonly used words in negative sentiments, including 'aplikasi', 'bagus', 'zen', 'banget', 'bisa', 'di', 'aku', 'download', 'Snapchat' and 'jelek'. The recurring mention of 'Snapchat' in negative reviews suggests a pattern where users often express dissatisfaction while specifically referencing the application.

Moreover, (Figs. 8-9) present word clouds depicting the terms used in either positive or negative sentiment reviews from TikTok users. The word cloud visually represents the frequency of words, with larger fonts indicating higher frequency. Figure (8) displays the positive sentiment word cloud, while Fig. (9) showcases the negative sentiment word cloud. These visualizations offer a comprehensive insight into the prominent themes and sentiments expressed by users in their reviews of the Snapchat application.

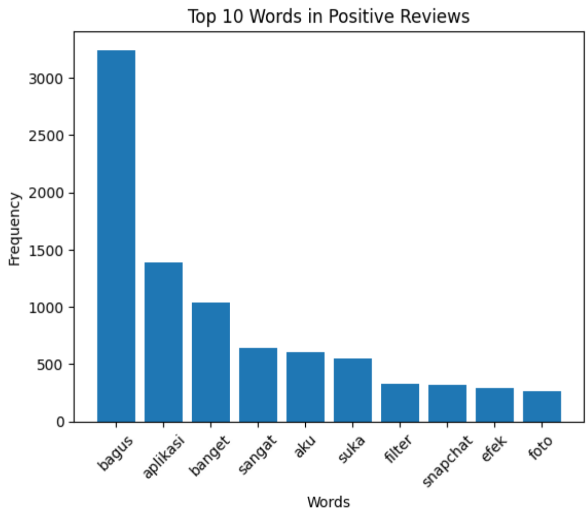

Fig. 6: Top 10 words in positive sentiment reviews

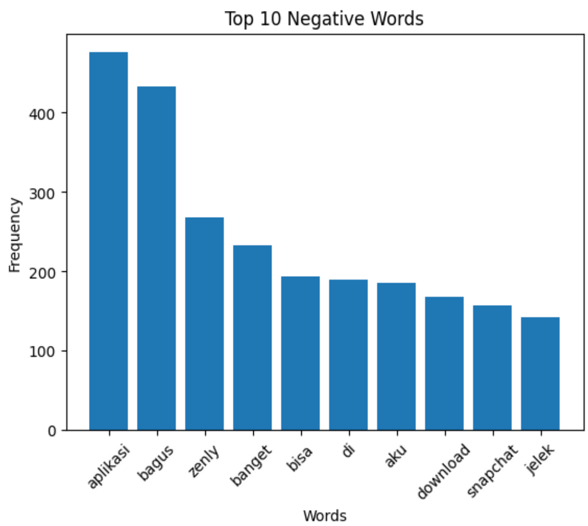

Fig. 7: Top 10 words in negative sentiment reviews

Fig. 8: Top 10 words in positive sentiment reviews

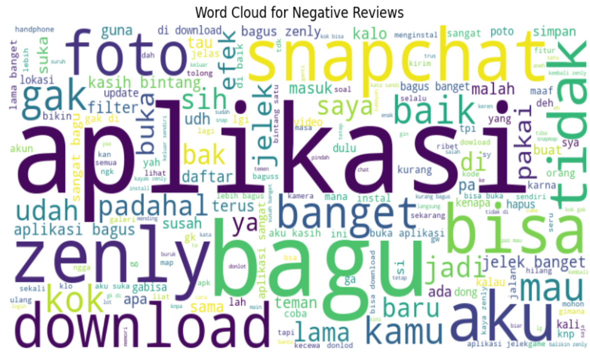

Fig. 9: Top 10 words in negative sentiment reviews

Conclusion

In conclusion, this research delved into the sentiment analysis of Snapchat user reviews within the Indonesian context, drawing upon a substantial dataset of 8015 user-generated reviews sourced from the Google Play Store. Employing a multi-faceted approach, the study harnessed advanced natural language processing techniques to preprocess and analyze the textual data, coupled with the implementation of diverse classification models. These models encompassed naive bayes, Support Vector Machines (SVM), and Random Forest, each contributing unique strengths to the sentiment classification process.

The findings of this investigation yielded valuable insights into the multifaceted landscape of user sentiment towards Snapchat among the Indonesian user base. By discerning the dominant sentiments expressed in reviews, the research elucidated the factors contributing to user satisfaction and dissatisfaction, thereby offering a comprehensive understanding of the prevalent attitudes towards the platform. Moreover, the identification of key themes associated with both positive and negative sentiments sheds light on specific aspects of Snapchat that resonate with or alienate users in this particular demographic.

With a robust sample size of 8015 user-generated reviews, the performance of the various classification models was evaluated based on their accuracy in predicting sentiment labels. The naive bayes models demonstrated an accuracy of 80%, while the SVM models achieved a slightly higher accuracy of 81%. Notably, the random forest model exhibited the most promising performance, attaining an accuracy of 83%. These results were further contextualized through a comparative analysis with existing literature, revealing potential avenues for future research endeavors in the domain of sentiment analysis within the Indonesian social media landscape.

A granular examination of frequently mentioned words within both positive and negative reviews unveiled specific attributes that users either lauded or criticized in relation to Snapchat. Positive reviews often highlighted terms such as 'bagus' (good), 'suka' (like), and 'efek' (effects), indicative of user appreciation for the platform's features and overall experience. Conversely, negative reviews frequently incorporated words like 'jelek' (bad) and alluded to technical issues pertaining to 'download' problems, underscoring areas where the app could be improved to enhance user satisfaction.

Overall, this research contributes to the expanding body of knowledge surrounding sentiment analysis in social media, particularly within the Indonesian context. The insights gleaned from this study not only offer valuable feedback for Snapchat developers but also provide a foundation for future research to explore the nuances of user sentiment and its implications for the broader landscape of social media platforms and their user communities.

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Author's Contributions

Evaristus Didik Madyatmadja: Led the research project, coordinated the development team, conducted experiments, instructed, performed data analysis, and authored the manuscript.

Fathya Putri Yasmina, Feladiva Annrastia Adrian, Brigita Christabel Surya Winata, Evelyn Pradhan, and Raihan Mahardhika: Provided research project advisement, designed the application, and conducted data analysis.

Christian: Reviewed and revised the manuscript, and approved the final version.

David Jumpa Malem Sembiring: Contributed to manuscript writing and proofreading.

Ethics

The authors confirm that this manuscript has not been published elsewhere and that no ethical issues are involved.

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