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Sentiment analysis spotify applications on google play store with naïve bayes and neural network methods

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ABSTRACT

Digital advancements have significantly changed the way music is accessed and enjoyed, with streaming platforms such as Spotify emerging as one of the most widely used applications worldwide. Along with this growth, user reviews on platforms like the Google Play Store have become an important source of information, offering insights into user satisfaction and areas for improvement. In this study, sentiment analysis was conducted on Spotify reviews using two classification methods, Naïve Bayes and Neural Networks. The reviews were collected, processed, and then analyzed with both approaches to evaluate their performance. The results show that Neural Networks outperformed in terms of accuracy, F1-score, and recall, while Naïve Bayes performed better in AUC, precision, and MCC. Analysis of the dataset also revealed that negative reviews dominated at 52.8%, followed by positive at 28.3%, and neutral at 19%. These findings highlight the value of sentiment analysis in understanding user perspectives and can support developers in improving application quality and user experience.

1. Introduction

Digital technology has changed the way we access and enjoy multimedia content, including music. Today, Spotify is the most popular music streaming platform in the world with 345 million users [1]. As the use of this application rises so does the role of reviews by users that are posted on application distribution platforms like Google Play Store [2]. Such reviews will be of help to application developers and at

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the same time, offer new user direction as to which application best meets a certain need [3]. Sentiment analysis is the method of assessment and the determination of the perceptions or attitudes that users have about the application distribution platform anchored on their reviews. Classification of the collected opinions in the form of textual user reviews is the goal of this study; the opinions will be classified in the positive, negative and neutral categories. Hence, the knowledge of user feelings can help the application developers to comprehend the merits and demerits of the applications developed by them and the areas that require enhancement [4].

The techniques often applied in sentimental analysis include the application of Naïve Bayes and Neural Network [5]. While it is rather basic, it is useful in most cases in order to address the tasks of text classification [6]. In contrast, another group of techniques, which is neural networks and more specifically deep learning, represent a more profound and intricate way of working with data. They are able to handle more complex relationships in the data and generally yield better performance in complicated classifications [7]. For the sake of the given case of the Spotify app review, the application of sentimental analysis using Neural Network and Naïve Bayes will entail a better understanding of the user sentiments. Each of the above-mentioned analysis types has its advantages and drawbacks [8].

Previous studies investigating sentiment analysis of Spotify app reviews on the Google Play Store have applied a variety of machine learning techniques with notable outcomes. Triyono et al. employed the Naïve Bayes algorithm to classify Spotify review sentiments into positive, negative, and neutral categories, following standard preprocessing and TF-IDF feature weighting; their model demonstrated effective classification performance in handling large unstructured dataset [9]. Madyatmadja et al. conducted a comparative assessment leveraging Naïve Bayes, Support Vector Machine (SVM), and Random Forest on over 14,000 Spotify reviews, finding that SVM achieved the highest performance with an F1-score of 0.875 and accuracy of 0.874, outperforming Naïve Bayes and Random [10].

This research will seek to compare and determine the efficiency of the two methods in categorizing the feelings of the Spotify app reviews. Thus, making this comparison we will be able to distinguish which approach is more effective and objective in recognizing feelings in app review. Thus, it is hoped that it will also be beneficial to enhance methodologies for better sentiment evaluation and offer significant information to assist developers in enhancing the efficiency and friendliness of their applications.

2. Method

The research steps are described in Figure 1.

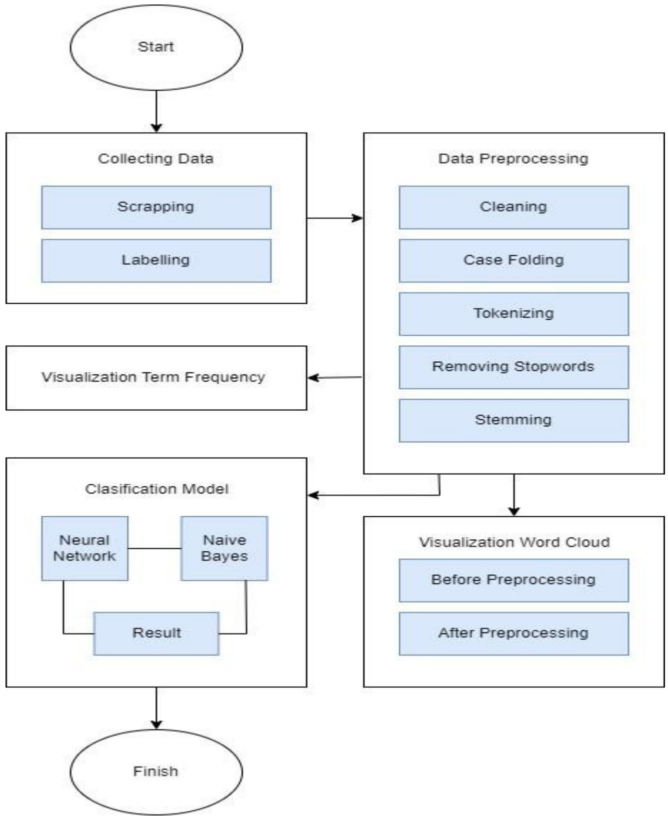

Figure 1. Research steps

Collecting Data

Data collection of Spotify app reviews from the Google Play Store is done using Python programming language using the 'google-play-scraper' library. The parameters used in this data collection process are as follows: language (lang) is set to 'id' for Indonesian, country (country) to'id 'for Indonesia, sequence (sort) set to Sort.NEWEST to sort reviews from the latest, and the number of reviews (count) has been set to 1000 [11]. Once the data has been successfully taken, only the relevant data is stored for this study, which is the latest review data until 15 May 2024. Next, each review is labeled sentiment based on the ratings given by the user. Rating 1 and 2 as negative sentiment, rating 3 as neutral sentiment, and rating 4 and 5 as positive sentiment. This labelling process allows sentiment analysis to be carried out automatically using available rating information.

Data Pre-processing

In this research, the review data undergoes a pre-processing phase to ensure the text is clean and ready for further analysis [12]. The process begins with data cleaning, which involves removing irrelevant characters such as unnecessary special symbols, numbers, punctuation marks, and excessive spaces to achieve a consistent text format. Next, case folding is applied to convert all letters into lowercase, ensuring that differences in capitalization do not affect the analysis [13]. The text is then tokenized into smaller units called tokens, typically words, which facilitates subsequent steps such as stopword removal and stemming [14]. Stopword removal is carried out to eliminate common words that carry little to no significance in text analysis, such as "and," "in," "to," and "that," so that the analysis can focus on more meaningful terms. Finally, stemming is performed to reduce words to their root form by removing affixes, thereby ensuring consistency and enabling the analysis to concentrate on the core meaning of each word [15].

Visualization Word Cloud

Word cloud is a visual representation of a set of words in which the most frequently appearing words are displayed in larger size and the words that appear less often are shown in smaller size. Word Cloud word size shows the frequency or importance of the word in the text: the more often the word appears, the larger the size [16]. This visualization helps in quickly understanding key words and major themes in a text set [17].

Word Cloud Before Pre-Processing

Word cloud before pre-processing is a visual representation of a collection of raw words without going through a pre-precessing stage such as stopword deletion, stemming, or normalization. In other words, this is a visualisation of the original text before further processing. This visualization provides an initial overview of the review text, but may be less informative due to the presence of irrelevant words.

Word Cloud After Pre-processing

This Word Cloud shows the words that often appear after the review text is processed. The words displayed are clear of special characters, numbers, and stopwords. Moreover, type and case has also been changed, making the words in basic form with the small letters. This visualization is rather more effective because the words that are not significant are not shown at all.

Visualization Term Frequency

TF is one of the methods of text analysis, which reflects the percentage of the frequency of a particular word to the overall number of words in a document. In text analysis, TFs are employed as a means of making the frequently used and significant words in a corpus to stand out [18].

Clasification Model

Classification is another approach that was employed in this study with the two models: Neural Network and Naïve Bayes employed to categorise data obtained from Spotify application reviews. Neural Network is a computing model based on the anatomy and working of the biological neural networks of human beings. This model is used for big and non-linear data and it is necessary large amount of computer resources for the training of the model. On the other hand, Naïve Bayes is a probabilistic based classifier which comes essentially from the Bayes Theorem and assumes that all of the features in the datasets are independent from each other [19]. This model is easier to implement, faster in training, but performance can be affected if the assumptions of feature independence are not met [20]. By understanding the characteristics and matches of each model, researchers can choose the model that best suits the purposes of the analysis and the data characteristics they have.

Evaluation Metrics

This study evaluates the model's performance using several metrics, namely AUC, CA, F1-score, Precision, Recall, and MCC. The Area Under the Curve (AUC) reflects the model's capability to distinguish between different classes, with higher values indicating better classification results. Classification Accuracy (CA) shows the percentage of correctly predicted instances out of the total data, providing a general measure of performance. The F1-score, which is the harmonic mean of Precision and Recall, offers a balanced assessment that is particularly important when dealing with imbalanced datasets. Precision indicates the proportion of true positive predictions among all predicted positives, while Recall shows the proportion of true positives identified out of all actual positives, both of which highlight the trade-off between false positives and false negatives. Lastly, the Matthews Correlation Coefficient (MCC) provides a more robust evaluation by taking into account all four outcomes: true positives, true negatives, false positives, and false negatives, making it especially valuable for imbalanced data. Collectively, these metrics deliver a thorough understanding of the model's classification performance.

3. Results and Discussion

After scraping Spotify app review data in the Google Play Store, we managed to collect a total of 796 reviews. Each review contains information about the review date (at), the application version when the review was made (reviewCreatedVersion), the review author's name (Username), the given rating (score), and the content of the review (konten). However, for this research, we only use review content and rating data. The tagging of reviews is based on the ratings given by the user [21]. Rating 1 and 2 as negative sentiment, rating 3 as neutral sentiment, and rating 4 and 5 as positive sentiment. This labelling process allows us to perform sentiment analysis automatically using existing rating information. The review labelling results showed a varied distribution of sentiment. The percentage of each category of sentiment is visualized in Figure 2 below.

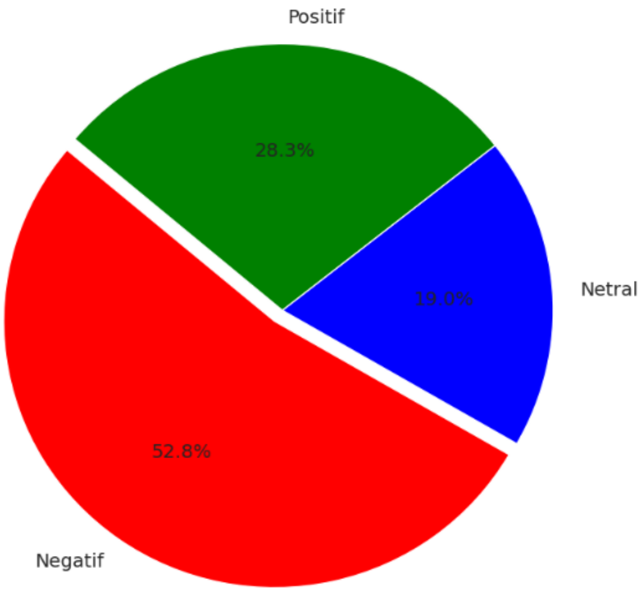

Figure 2. Sentiment presentation

Out of a total of 796 successful reviews collected, 420 reviews were categorized as negative sentiment, including reviews with ratings 1 and 2. Reviews with neutral sentiment, which has a rating of 3, totaled 151 reviews. Meanwhile, reviews with positive sentiment, that include ratings 4 and 5, totaled 225 reviews. This distribution shows that the majority of users provide reviews with a negative sentiment, which is 52.8%. Reviews with a positive sentiment followed by a percentage of 28.3%, and reviews with neutral sentiment of 19%. These results describe that more than half of user reviews tend to be negative, while positive and neutral reviews occupy a smaller portion.

After tagging the review data, the next step is to perform pre-processing using the Orange application to prepare the data before further analysis. This process involves a series of phases of text cleaning, such as reading mark removal, tokenization, stopwords removal and text normalization, aimed at ensuring consistency in word representation. In addition, advanced text processing techniques such as stemming or lemmatization are also applied to mitigate word variation. After completing preprocessing, visualize using word cloud for all review text before and after preprocesing [22]. The processing circuit can be seen in Figure 3.

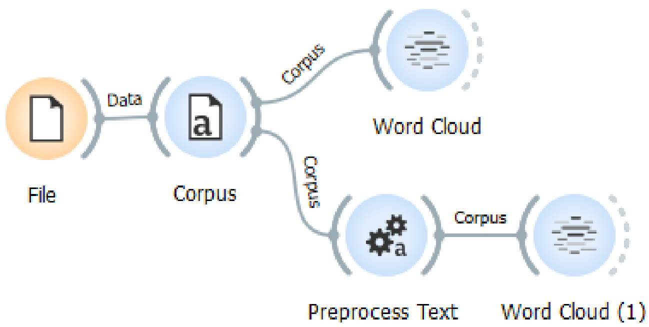

Figure 3. Processing circuit

Word cloud before pre-processing is a visualization of the most frequently appearing words in the reviews, providing a direct overview of the word usage without any changes. Word cloud after the pre-Processing process provides an overview about the remaining keywords after the cleaning process is completed.

Figure 4. Before Preprocessing

Figure 5. After preprocessing

Figure 4 is a word cloud before the preprocessing process, whereas Figure 5 is the word cloud after the preprosessing process. There is a significant difference that reflects the preprocessing process that has been carried out. Figure 5 shows the word cloud after the process, where it can be observed that no more readmarks, numbers, emoticons, or other words and readmarks are unnecessary [23]. This indicates that the text cleaning steps performed in preprocessing have successfully removed irrelevant elements from the review text. Thus, word cloud after preprocessing provides a clearer visual representation and more focus on keywords that are important in user reviews. These differences describe the effectiveness of preprocessing in preparing data in a more accurate and consistent way for further sentimental analysis.

This is followed by frequencies being visualized on the each positive, neutral and negative label. The selection of the most suitable frequency terms is used in every phase of textual data analysis and is especially significant in the case of sentimental analysis, for example in previously included Spotify application for iphone. It is very easy for it to distinguish between the frequently appearing words and most significant words that contribute in determination of sentiment within the given data set. In addition, there is the benefit of visualization in uncovering the further patterns or trends, which are not clearly visible in the data for the next actionable steps to be taken. Therefore, besides being an effective way of gaining a more profound understanding of data, the term frequency visualization also helps convey the extracted information more clearly and concisely between the analyst and the consumer of the text analysis results [24].

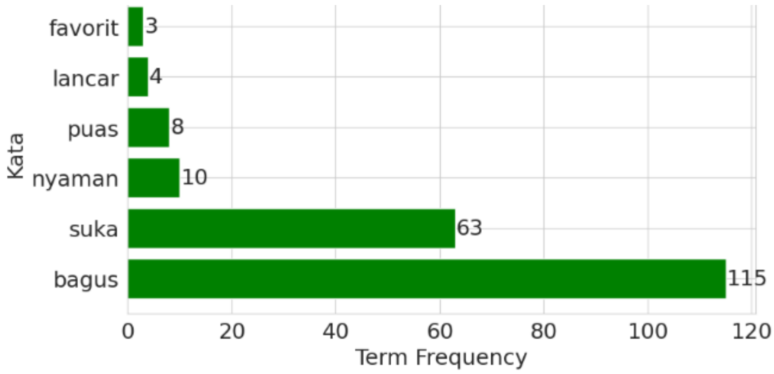

Figure 6. Frequency words positive sentiment

Figure 6 shows the distribution of the frequency of appearance of keywords associated with positive sentiment in the Spotify app reviews. The most dominant keyword is "bagus (good)", with a 115-fold occurrence rate, which indicates that users often refer to the app as good. Then, the keyward "suka (like)" also appears quite often at a frequencies of 63 times, indicating that many users express satisfaction or pleasure in using the app. On the other hand, the key words "lancer (fluent)", "nyaman (comfortable)", "favorit (favorite)", and "puas (statisfy)" appear with lower frequences, each with 4, 10, 3, and 8 times. Although these keywards appear less often, they still contribute positively to the overall impression given by users to the spotify app. Thus, from this visualization, it can be concluded that the majority of the reviews of the app that have been given positive sentiment highlight the quality and satisfaction of the user's experience using this app, with the key word "bagus (good)" being the most striking.

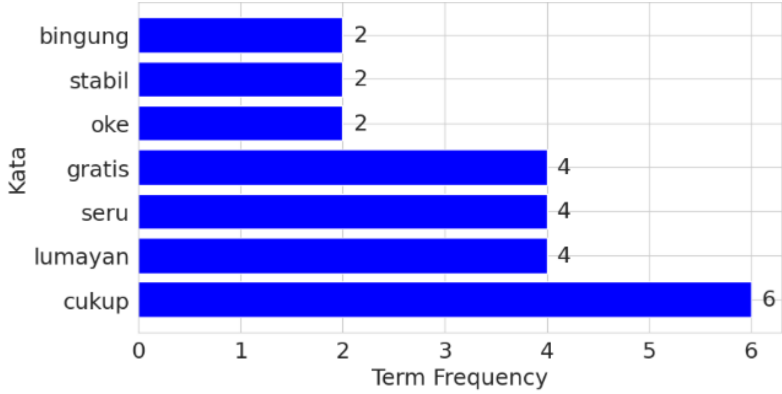

Figure 7. Frequency words neutral sentiment

In Figure 7 shows a bar diagram showing the frequency distribution of occurrences of keywords associated with neutral sentiment in Spotify app reviews, there are a number of key words that appear with varying frequencies. The keyword "cukup (enough)" is the most frequently appearing with a frequency of 6 times, which indicates that some users give a neutral assessment of this application, considering it quite good or adequate. Next, the keywords "lumayan (reasonable)", "seru (exciting)", "gratis (free)", and "bingung (confused)" appear with the same frequencies, i.e. 4 times. This indicates a variety of responses from users, some of whom consider the experience using the app to be quite satisfactory ("lumayan"), some find the features interesting ("seru"), and others appreciate the fact that the app is free to use. On the other hand, the keywords "oke" and "stabil (stable)" appear with lower frequencies, only 2 times each. Nevertheless, the keyword also contributes to the overall picture of the neutral sentiment towards the Spotify app. From this visualization, it can be concluded that reviews labeled neutral sentiment tend to show feelings that are not too extreme, with users expressing a diverse view of the app, both positive and neutral.

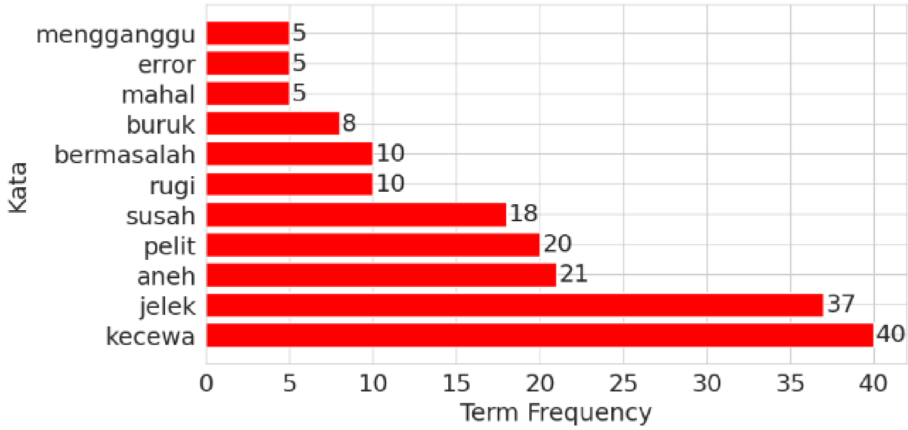

Figure 8. Frequency of negative sentiment words

From a bar diagram that depicts the frequency distribution of the occurrence of keywords associated with negative sentiment in the Spotify app reviews, it can be seen that there are a number of key words that appear with varying frequencies. The keywords "jelek (bad)" and "kecewa (disappointed)" are the most frequently appearing with frequencies of 37 and 40 respectively. This indicates that most users express their dissatisfaction with the quality or experience of using this application. Moreover, the keyword "susah (hard)" also appears with a fairly high frequency, namely 18 times, indicating the difficulties experienced by users in using or accessing the features of the Spotify application. Other keywards such as "aneh (stange)" (21), "pelit (stingy)" (20), and "rugi (loss)" (10) also appear with a significant Frequency indicating a variety of insatisfactions and problems that users have encountered in using this app. Although some keybords like "mahal (expensive)" or "error" appear at a lower frequenity, 5 times each, they still contribute to highlighting negative aspects in Spotify app reviews. It provides an overview that needs to be fixed or enhanced by application developers to increase user satisfaction and reduce the level of dissatisfaction.

The purpose of the evaluation is to measure how effective the model is in predicting data that has never been seen before. By evaluating the performance of the model, the researcher can find out how accurate it is in classifying the data, comparing the different models to choose the best one, and identifying areas that need to be improved to improve performance. Evaluation also helps in detecting potential problems such as overfitting or underfitting, which can reduce the reliability of model predictions. The evaluation of the performance of the classification model can be seen in Figure 9.

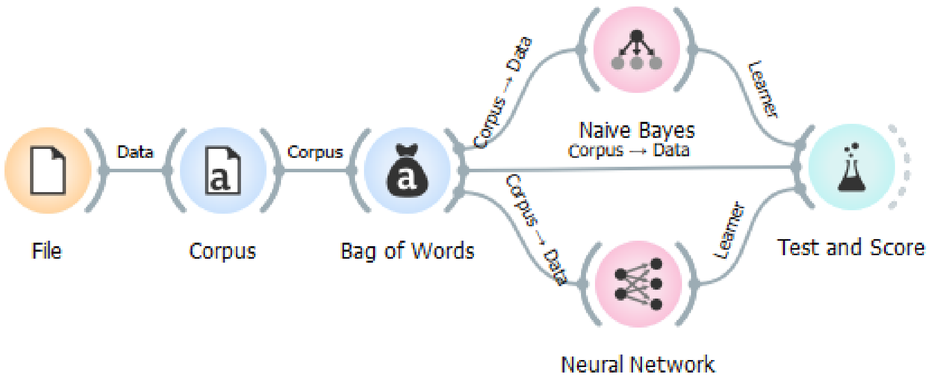

Figure 9. Performance evaluation circuit classification model

Table 1. Results of performance assessment

Model	AUC	CA	F1	Precision	Recall	MCC
Neural Network	0.774	0.769	0.754	0.754	0.769	0.381
Naïve Bayes	0.791	0.688	0.704	0.779	0.688	0.412

Table 1 shows the results of the evaluation of the Neural Network and Naïve Bayes classification models. In evaluating the performance of these two models of classification, the researchers used the method of cross-validation with 10fold, some important evaluation metrics used to give a comprehensive understanding of the capabilities of both. First, in terms of AUC or Area Under Curve, Naïve Bayes showed a slightly higher score (0.791) compared to the Neural Network (0.774), marking a small advantage in distinguishing positive and negative review classes based on the ROC curve. However, when we look at Classification Accuracy (CA), which measures the proportion of the correct prediction of the overall prediction, Neural Networks outperformed with a score of 0.769, compared with 0.688 of the Naïv Bayes. Furthermore, the F1 Score gives an overview of the balance between Precision and Recall; Neural networks have a higher F1 score of (0.754) comparing to the Naiv Bayes (0.704), showing a better balance in identifying positive reviews accurately and detecting as many positive reviews as possible. Although Naïves Bayes achieves a higher Precision of 0.779 than the Neurals Networks (0.75.4), Network Recall has a higher score of 0.079. Finally, the Matthews Correlation Coefficient (MCC), which measures the correlation between predictions and actual labels, shows a slight advantage of Naïve Bayes (0.412) over Neural Network. (0.381).

Overall, the results of this evaluation show that each model has relative advantages and weaknesses depending on the evaluation metrics considered. In this study Neural Network showed better performance in terms of accuracy, F1 Score, and Recall, while Naïve Bayes outperformed in AUC, Precision, and MCC. It altogether depends on the metric which suits for a particular sentimental analysis workload.

4. Conclusion

Advances in digital technology have reshaped how users interact with multimedia applications, making user reviews on platforms like the Google Play Store an important source of insight. In the case of Spotify, sentiment analysis was applied to classify user opinions using Naïve Bayes and Neural Network methods. From 796 collected reviews, the majority expressed negative sentiment (52.8%), followed by positive (28.3%) and neutral (19%). Evaluation results showed that Neural Networks performed better in accuracy, F1-score, and recall, while Naïve Bayes was superior in AUC, precision, and MCC. These findings suggest that the most suitable method depends on the evaluation metrics prioritized in the analysis. Overall, the study contributes to the advancement of sentiment analysis techniques and provides useful guidance for developers in enhancing application quality and user experience.

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