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Sentiment Analysis of Bapenda South Sulawesi Mobile Application on Google Play Store Using Support Vector Machine

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ABSTRACT

This study analyzes user sentiment toward the Bapenda Sulsel Mobile application, an e-government platform developed by the Regional Revenue Agency of South Sulawesi, Indonesia. The research aims to evaluate user feedback and identify areas for improvement to enhance user satisfaction. Using sentiment analysis, user reviews from Google Play Store were collected and classified into positive, negative, and neutral sentiments through the Support Vector Machine (SVM) algorithm. Preprocessing steps such as tokenization, stopword removal, and stemming were applied to prepare the data. Term Frequency-Inverse Document Frequency (TF-IDF) was used for feature extraction to enhance classification accuracy. The SVM model demonstrated an overall accuracy of 80%, achieving a high recall of 98% for positive reviews but only 40% for negative reviews, reflecting challenges in handling class imbalance. Results show that 72% of users expressed positive sentiment, praising the app's functionality and ease of use. However, 28% of reviews were negative, citing issues like technical bugs and usability challenges. The findings highlight the app's strengths in delivering e-government services and its role in improving tax management. However, the significant proportion of negative feedback emphasizes the need for addressing user concerns. Recommendations include balancing the dataset, refining the SVM model, and prioritizing improvements based on user feedback. This study contributes to the broader understanding of applying sentiment analysis in evaluating e-government platforms and offers actionable insights for enhancing the user experience.

Keyword: Sentiment Analysis; Support Vector Machine; Mobile Applications; User Feedback; Play Store.

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1. Introduction

In the age of digitalization, government institutions are increasingly adopting technology to improve the efficiency of their services. One such initiative is the Bapenda Sulsel Mobile application, developed by the Regional Revenue Agency (Bapenda) of South Sulawesi, Indonesia. This application aims to facilitate tax payments, provide information on regional revenue, and offer various other services to ease interactions between citizens and local authorities. As part of the broader push towards e-governance, mobile applications like Bapenda Sulsel are seen as vital tools to improve transparency, accessibility, and efficiency in government operations (Bapenda Sulawesi Selatan, 2021).

However, the success of such an application is not determined solely by its functionality, but also by the users' perception and experience. In the digital age, users often voice their opinions, both positive and negative, about mobile applications through various online platforms, especially in app reviews. These reviews contain valuable insights that can be used to assess the overall performance of the application, identify technical issues, and understand user satisfaction (Seftiawan & Kurniawan, 2022). Therefore, analyzing user sentiment towards the Bapenda Sulsel Mobile app is crucial for understanding its impact and guiding future improvements.

Sentiment analysis, a field within Natural Language Processing (NLP), enables the automatic extraction and classification of opinions from textual data(Khurana et al., 2023). By applying sentiment analysis to user reviews, we can quantify the overall sentiment and categorize feedback into positive, negative, or neutral. This process provides actionable insights that developers can use to enhance the app’s performance and user experience. Traditionally, sentiment analysis has employed various machine learning algorithms, such as Naïve Bayes, Decision Trees, and Support Vector Machine (SVM), each offering distinct advantages in terms of accuracy and computational efficiency (Isnan et al., 2023).

Among these methods, SVM has emerged as a particularly powerful tool for text classification tasks, including sentiment analysis. SVM operates by constructing hyperplanes in a multidimensional space that separates different classes of data. It is especially effective in dealing with high-dimensional datasets, such as those encountered in text mining, where each word or term can be considered a feature (Nasution & Khodra, 2017). With its strong theoretical foundations and proven ability to generalize well on small, high-dimensional datasets, SVM has become a preferred choice for many sentiment analysis applications.

This study aims to conduct a sentiment analysis of user reviews of the Bapenda Sulsel Mobile application using the SVM algorithm. By leveraging this method, we seek to evaluate the overall sentiment expressed by users and identify the key areas of concern or praise within the app. Through this analysis, we aim to provide insights that will help the developers of Bapenda Sulsel Mobile to improve the application's usability, fix any identified issues, and ultimately enhance user satisfaction. Furthermore, the findings from this study will contribute to the broader understanding of how sentiment analysis can be applied to e-government platforms, highlighting its importance in shaping the future of digital public services (Hao et al., 2023).

Given the increasing reliance on mobile technology for public service delivery, it is essential to ensure that these applications meet user expectations. Negative sentiments, if left unaddressed, can result in poor adoption rates and a decline in the application's credibility. Therefore, this research also serves a practical purpose by offering concrete suggestions based on user feedback to improve the Bapenda Sulsel Mobile app, ultimately supporting the South Sulawesi government's goals for efficient, technology-driven public service.

2. Method

This section describes the steps taken to conduct the sentiment analysis on user reviews of the Bapenda Sulsel Mobile application. The method involves several stages, including data collection, preprocessing, feature extraction, and model implementation using Support Vector Machine (SVM).

The data used in this research consists of user reviews from the Google Playstore for the Bapenda Sulsel Mobile application. Reviews were collected through web scraping techniques, with user ratings and comments being the primary focus. The dataset was sourced from the Google Playstore, comprising approximately 1,500 user reviews collected over the period from January 2020 to August 2024.

Data preprocessing is a crucial step to clean and prepare raw text data for analysis, ensuring it is suitable for further processing. This process involves several steps, starting with tokenization, where text is split into individual words or tokens to facilitate analysis at the word level. Next, all text is converted to lowercase to maintain uniformity and prevent discrepancies due to capitalization. Stopword removal is then applied to eliminate common words such as "and," "the," and "is," which do not carry meaningful sentiment information and may dilute the analysis. Stemming follows, which reduces words to their root forms, such as converting “running” to “run,” thereby standardizing variations of the same word (Sun et al., 2024). Lastly, noise removal is performed to eliminate non-textual elements like symbols, numbers, and special characters, which do not contribute to the sentiment analysis, resulting in a cleaner and more relevant dataset for model training and evaluation.

In this study, the Term Frequency-Inverse Document Frequency (TF-IDF) technique was employed to transform text data into numerical features suitable for classification using the Support Vector Machine (SVM) algorithm. The TF-IDF method combines two components: Term Frequency (TF) and Inverse Document Frequency (IDF). Term Frequency measures how often a term appears in a specific document, calculated as $TF(t,d) = \frac{f(t,d)}{N_d}$, where $f(t,d)$ represents the frequency of term *t* in document *d*, and N_d is the total number of terms in d. In contrast, Inverse Document Frequency assesses the importance of terms by reducing the weight of frequently occurring words across multiple documents, defined as $IDF(t) = log(N / (1 + |\{d \in D : t \in d\}|))$, where N is the total number of documents, and $|\{d \in D : t \in d\}|$ denotes the number of documents containing term *t*. The final $TF - IDF$ score for a term is computed as the product of *TF* and *IDF*, $TF - IDF(t,d) = TF(t,d) \times IDF(t)$. This approach effectively emphasizes terms that are unique and informative for individual documents while downplaying terms that are common across the dataset, thereby enhancing the quality of features used for sentiment classification (Cahyani & Saraswati, 2023).

Support Vector Machine (SVM) is employed to classify the sentiment of each review as positive, negative, or neutral by identifying an optimal hyperplane that separates the data into distinct classes. SVM operates by solving an optimization problem, where the goal is to minimize $(\frac{1}{2}) * ||w||^2$, subject to the constraint $y_i\ (w^T x_i + b) \geq 1$ for all i. Here, w represents the weight vector, b is the bias term, y_i denotes the class label for the i-th review (+1 for positive and -1 for negative), and x_i is the feature vector for the i-th review. By maximizing the margin between the two classes, SVM ensures the best possible separation between positive and negative sentiments. This method is particularly effective for handling high-dimensional data and has proven to be robust for text classification tasks, such as sentiment analysis (Obiedat et al., 2022).

To evaluate the performance of the SVM model, several metrics were employed. Accuracy, calculated as the percentage of correctly classified reviews, provides a general measure of the model's performance. Additionally, precision, recall, and F1-score were used to offer a more detailed evaluation, especially when dealing with imbalanced datasets. Precision measures the percentage of correctly predicted positive observations out of all observations predicted as positive, while recall calculates the percentage of correctly predicted positive observations out of all actual positives. The F1-score, the harmonic mean of precision and recall, combines these metrics into a single value to balance their trade-offs.

The performance of the SVM model was further assessed using a confusion matrix to visualize correct and incorrect classifications across sentiment categories. For the implementation of this research, Python was utilized as the programming language, with Scikit-learn for building machine learning models, Pandas for data handling, and Matplotlib for creating visualizations.

3. Result and Discussion

The sentiment analysis using Support Vector Machine (SVM) yielded the following results based on the test dataset:

Table 1. SVM Result

Sentiment	Precision	Recall	F1-Score	Support
Negative	91%	40%	56%	25 reviews
Positive	79%	98%	87%	56 reviews
Overall Accuracy			**80%**	

SVM model demonstrated reasonable performance in classifying sentiment, achieving a high recall of 98% for positive sentiment, suggesting that most positive reviews were correctly identified. However, the model faced challenges with negative sentiment, attaining only a 40% recall, indicating that many negative reviews were not classified correctly. This imbalance in performance is likely due to the dataset's skew, with more positive reviews than negative ones. Despite the high precision of 91% for negative sentiment, which means that when the model predicted a review as negative, it was mostly correct, the low recall highlights that many negative reviews were missed. The F1-score, which balances precision and recall, was higher for positive sentiment (87%) compared to negative sentiment (56%), further reflecting the model's stronger performance with positive reviews. To address these issues, potential improvements include applying data balancing techniques, such as oversampling negative reviews or undersampling positive ones, to correct the class imbalance. Additionally, experimenting with different SVM kernels, like the Radial Basis Function (RBF), or integrating other machine learning models, such as Random Forest or Gradient Boosting, could further enhance accuracy and improve the model’s ability to classify negative sentiment more effectively.

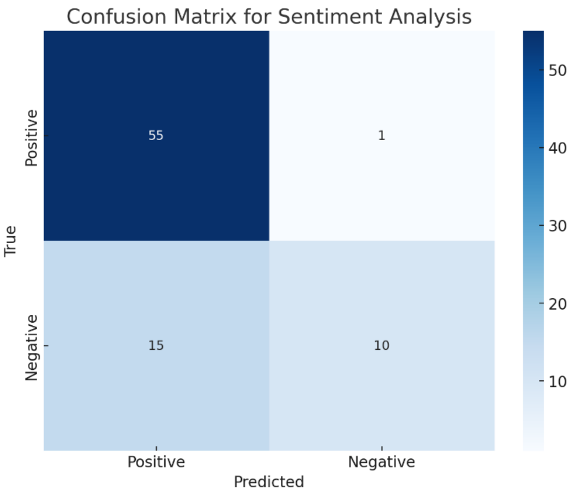

Figure 1. Confusion Matrix for Sentiment Analysis

The confusion matrix provides a clear visualization of the SVM model's performance in predicting sentiment. It displays how well the model classified both positive and negative sentiments. In the matrix, the top-left cell (True Positive) indicates the number of positive sentiments that were correctly predicted, while the bottom-right cell (True Negative) shows the number of negative sentiments that were correctly identified. The off-diagonal cells highlight the misclassifications: positive reviews that were incorrectly predicted as negative (top-right) and negative reviews that were mistakenly classified as positive (bottom-left). This visualization underscores the model's strength in accurately identifying positive reviews, but it also reveals challenges in correctly classifying negative reviews, indicating areas for potential improvement in handling negative sentiment.

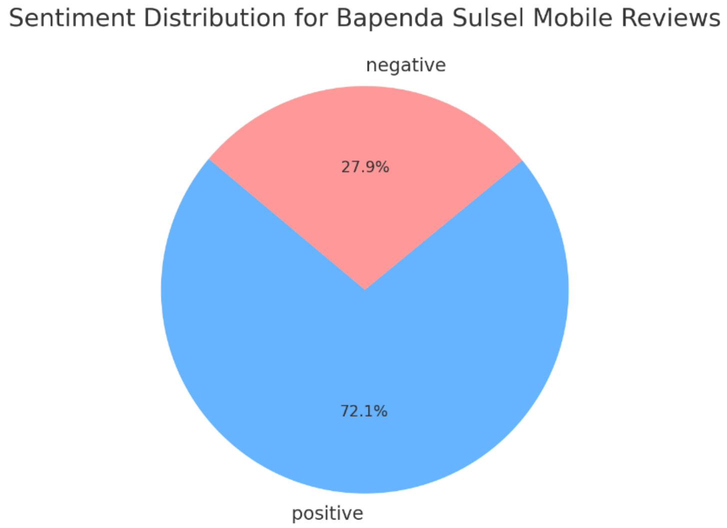

Figure 2. Sentiment Distribution

Table 2. Sentiment Analysis

Sentiment	Count
Negative	289
Positive	112

The sentiment analysis results, represented visually in a pie chart, reveal a clear distribution of positive and negative sentiments in user reviews of the Bapenda Sulsel Mobile application. Of the total reviews, 289 (approximately 72%) reflect positive sentiment, indicating that the majority of users are satisfied with the app. Positive reviews often highlight aspects such as ease of use, functionality, responsiveness, and reliability, with users particularly appreciating the app's ability to help manage taxes and access regional services conveniently through their mobile devices. This consistent trend in positive feedback suggests that the app largely meets user expectations and delivers on the services it promises. However, 112 reviews (approximately 28%) expressed negative sentiment, pointing to dissatisfaction with certain features of the app, such as technical issues, usability challenges, and unmet user expectations. Users who gave low ratings (1 or 2 stars) commonly cited problems like app crashes, incorrect data, or difficulties during registration or payment processes. While the app has generally been well-received, the significant proportion of negative reviews highlights areas for improvement. These unresolved issues could hinder the app's wider adoption and impact its reputation over time, emphasizing the need for developers to address these concerns to improve the overall user experience and maintain user trust.

The data reveals several important insights about the Bapenda Sulsel Mobile app. First, the majority of users have a positive reception, with 72% of reviews reflecting satisfaction. This indicates that the app has a solid foundation in terms of functionality and provides valuable services to many users. However, with nearly 28% of reviews being negative, it's clear there are pain points that need attention. Common issues mentioned in negative reviews, such as poor performance, usability challenges, or technical bugs, should be prioritized by developers to enhance the app's performance and user experience, which could help mitigate the negative sentiment. Furthermore, the app is in a good position for potential growth. By addressing the concerns raised in the negative reviews, developers can increase user retention, reduce dissatisfaction, and promote positive word-of-mouth, ultimately leading to a better overall rating. In conclusion, while the app has a strong user base, there are clear opportunities for improvement. These findings suggest that focusing on the issues highlighted in the negative feedback can help improve the app's performance, increase user satisfaction, and enhance its positive reception moving forward.

4. Conclusion

This research conducted a sentiment analysis on user reviews of the Bapenda Sulsel Mobile application using the Support Vector Machine (SVM) algorithm to classify feedback into positive and negative sentiments, providing valuable insights into the overall user experience. The conclusions drawn from this study are as follows:

High User Satisfaction (72% Positive Sentiment): The majority of the user reviews (72%) expressed positive sentiment, indicating that the Bapenda Sulsel Mobile application has been well-received by most users. This suggests that the app generally meets user expectations in terms of functionality, reliability, and ease of use. Positive feedback often praised the app for being helpful in tasks such as managing regional taxes and accessing information efficiently. This strong positive sentiment highlights the app's value and its role in supporting e-government initiatives in South Sulawesi.

Significant Proportion of Negative Sentiment (28%): Despite the generally positive reception, a notable 28% of the reviews reflected negative sentiment. These reviews indicate dissatisfaction with aspects such as technical difficulties, usability challenges, and inaccuracies in the app's services. While these issues represent a smaller portion of the overall feedback, they are critical to address to ensure the app continues to grow and effectively serve its users. The high recall for negative sentiment (40%) suggests that a significant portion of dissatisfied users voiced their concerns, particularly regarding the app's performance and usability.

Support Vector Machine (SVM) Performance: The SVM model used in this study achieved an accuracy of 80%, with particularly strong performance in classifying positive sentiment (recall of 98%). This confirms that SVM is an effective method for sentiment classification in text-based reviews, particularly when the majority sentiment is positive. However, the lower recall for negative sentiment (40%) indicates room for improvement in balancing the dataset and refining the model to better capture less frequent negative feedback.

Areas for Improvement in the Application: The analysis identifies critical areas that developers should prioritize for improvement, such as addressing bugs or errors that disrupt user experience, improving data accuracy, and enhancing the app's overall usability. Focusing on these issues could help reduce the negative sentiment, increase user retention, and improve the app's overall rating.

Potential for Enhancing User Experience: The sentiment analysis provides actionable insights for enhancing the Bapenda Sulsel Mobile app. By analyzing the feedback and addressing the areas contributing to negative reviews, the development team can make informed decisions to enhance performance. This will not only improve the experience for existing users but also attract new users and build greater trust in the app's ability to deliver essential public services effectively.

Future Work to enhance the accuracy of sentiment classification, future studies could explore more advanced machine learning techniques, such as deep learning models like LSTM (Long Short-Term Memory) or BERT (Bidirectional Encoder Representations from Transformers), which have shown promising results in handling complex text data and capturing nuanced sentiment patterns. Additionally, experimenting with other classification methods could provide better solutions for handling imbalanced datasets, which were a challenge in this study. A more granular analysis of specific issues raised in the negative reviews, such as bugs, slow performance, or user interface difficulties, would also offer valuable insights for app improvement. This detailed analysis could help developers identify and prioritize the most critical areas to enhance user experience and overall app performance.

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