

Sentiment Analysis of Roblox Game Reviews on Google Play Store Using Lexicon-SVM Integration

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Abstract: The development of digital technology has driven changes in entertainment consumption patterns, especially among the younger generation. Roblox has become one of the most popular online gaming platforms, with a wide range of user opinions recorded on Google Play Store. This study aims to classify the sentiment of Roblox user reviews (positive, negative, neutral) and evaluate the performance of the Support Vector Machine (SVM) algorithm with TF-IDF weighting and automatic labeling using Lexicon InSet. Data was obtained by crawling 10,000 reviews during the period of April 2–May 23, 2025, and after the preprocessing stage, 8,950 data remained for analysis. The classification results show that the sentiment distribution consists of 41.3% positive (3,703 reviews), 41.8% neutral (3,739 reviews), and 16.8% negative (1,507 reviews). Model evaluation using a confusion matrix produced high performance with 87.03% accuracy, 87.29% precision, 87.03% recall, and an F1-score of 86.67%. WordCloud visualization shows that positive reviews emphasize creativity and interactive features, while negative reviews are dominated by technical complaints such as lag and errors. These findings prove that the combination of SVM, TF-IDF, and Lexicon InSet is effective in sentiment analysis and provides valuable input for developers to improve application quality and user protection. Further research is recommended to adopt a hybrid approach based on deep learning and aspect-based sentiment analysis to generate more insights.

Keywords: Sentiment Analysis, Support Vector Machine, Lexicon InSet, Google Play Store, Roblox

INTRODUCTION

The development of digital technology has had a significant impact on people's lifestyles, especially the younger generation who are increasingly utilizing internet-based entertainment platforms. One platform that is experiencing rapid growth is Roblox, an online game application that not only provides entertainment facilities, but also presents a space for social interaction and creativity development for its users. Through Roblox, players can create their own virtual worlds, share with the community, and participate in various games created by other users. According to Data Reportal, in the first quarter of 2022 Roblox recorded more than 54 million daily active users globally and was ranked as the seventh most popular mobile game in Indonesia (Yuliastika, T., & Fitriana, 2023). This fact shows that Roblox is not just a trend, but has also formed a culture of play among teenagers and children. Behind this popularity, there are a number of issues that have caused public concern. Problems that often arise include uncontrolled purchases of virtual items, the risk of exposure to content that is not age-appropriate, as well as bugs, technical glitches, and security issues that are often complained about by users (Alhasan, K., & Alhasan, 2023; Oh et al., 2024). In addition, in-app transactions that lack parental supervision raise concerns about the social and economic impact of using these apps (Ansyah, F., & Suryono, 2025). User reviews on the Google Play Store are a testament to these perceptions, reflecting satisfaction levels, technical complaints, and responses to policies and features. Data from these reviews is an important source of information for to analyze public views in greater depth. To understand these perceptions, sentiment analysis is used as an effective method in processing text-based opinions by classifying sentiments into positive, negative, and neutral categories (Al-Husna, G. S.,

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Asmarajati, D., Ihsannuddin, I. A., & Mahmudati, (2024) . Among various classification algorithms, Support Vector Machine (SVM) is known to excel in handling high-dimensional data and is able to produce optimal class separation(Aini, W. R., Sudipa, I. G. I., Sandana, I. P. D., Putra, D. M. D. U., & Indrawan, 2024; Sakshi et al., 2024) . This advantage has been proven by previous research, for example, conducted by(Utami et al., 2023) with 96.43% accuracy in sentiment analysis of gadget reviews, as well as research(Tinaliah, 2022) which recorded 79% accuracy on similar applications.

In addition to machine learning algorithms, lexicon-based approaches are also often used to strengthen the analysis, especially at the data labeling stage. InSet Lexicon, as one of the Indonesian sentiment dictionaries containing more than 10,000 words with positive and negative labels, is proven to help speed up and improve the accuracy of the labeling process(Fathoni, M. F. N., Puspaningrum, E. Y., & Sihananto, 2024; Natarajan et al., 2025) . The application of a combination of SVM, TF-IDF, and InSet-based labeling methods allows the analysis to be carried out effectively, accurately, and scalable for large datasets.

Recent studies have highlighted the competitiveness of SVM for online game reviews, such as sentiment analysis of Genshin Impact (Mr. Aldiansyah & Fuad, 2024), Lokapala (Ishar, 2024), and eFootball (Agustian, C., Hananto, A. L., Nurapriani, F., & Huda, 2025), showing accuracy rates between 79%–90%. Other works applied SVM with lexicon-based labeling to Play Store reviews of GoBiz (Firda, H., Putra, P., Oktadini, N. R., Sevdiyuni, P. E., & Meiriza, 2025), reporting accuracy above 87%. Hybrid approaches that combine InSet lexicon with deep learning models such as IndoBERT have also been proposed, achieving over 80% accuracy (Asri, Y., Kuswardani, D., Suliyanti, W. N., Manullang, Y. O., & Ansyari, 2025). These findings confirm both the relevance of SVM and the growing trend of integrating lexicon resources like InSet for Indonesian sentiment analysis. However, most previous research has focused on other applications and popular games, often using smaller datasets or single-method approaches. To date, no comprehensive study has applied a combination of SVM, TF-IDF, and InSet lexicon labeling specifically to Roblox with a large-scale dataset of 10,000 Google Play Store reviews. Therefore, this research fills that gap by proposing an integrated pipeline, evaluating classification performance using accuracy, precision, recall, and F1-score, and presenting visualizations (WordCloud) that provide actionable insights for developers. Thus, this study aims to classify the user sentiment of the Roblox application on the Google Play Store and evaluate the performance of the SVM algorithm supported by TF-IDF weighting and labeling using Lexicon InSet. The results of this study are expected to provide useful insights for developers in improving application quality, strengthen user protection policies, and become a reference for further research in the field of sentiment analysis and natural language processing.

Previous studies have focused on sentiment analysis of popular gaming applications such as Genshin Impact, Lokapala, and eFootball using SVM methods or hybrid approaches (Mr. Aldiansyah & Fuad, 2024); (Ishar, 2024); (Agustian, C., Hananto, A. L., Nurapriani, F., & Huda, 2025). Some studies have also applied lexicon-based labeling to other applications, such as GoBiz (Firda, H., Putra, P., Oktadini, N. R., Sevdiyuni, P. E., & Meiriza, 2025). However, to date, no study has combined SVM with InSet Lexicon to analyze Roblox reviews using a large dataset of 10,000 reviews. Therefore, this study contributes by (i) implementing an integrated pipeline of SVM, TF-IDF, and InSet Lexicon for large-scale sentiment classification, (ii) evaluating model performance through accuracy, precision, recall, and F1-score, and (iii) providing practical insights for developers through WordCloud visualization of user reviews. This research is expected to be an important reference for application quality development, user protection policies, and further studies in the field of sentiment analysis and natural language processing.

LITERATURE REVIEW

Sentiment analysis has become one of the most popular methods in understanding public opinion expressed through text data, especially in the context of app and online game reviews. It allows researchers to categorize opinions into specific sentiment categories such as positive, negative, and neutral. Among the various algorithms used in sentiment analysis, Support Vector Machine (SVM) is among the most widely adopted due to its ability to process high-dimensional data and produce optimal class separation(Dewi, Y. R., Saraswati, N. W. S., Monny, M. O. E., Sarasvananda, I. B. G., & Andika, 2025; Priadinata et al., 2025). The advantage of SVM lies in its use of a maximum-margin hyperplane, which enhances the model's generalization capability. The advantage of SVM lies in the use of a *hyperplane* with maximum margin that can improve the generalization ability of the model. A number of previous studies have implemented SVM in various sentiment analysis scenarios. (Iriananda, S. W., Budiawan, R. W., Rahman, A. Y., & Istiadi, 2024)For example, optimizing the sentiment classification of mobile game user comments by combining SVM, *grid search*, and *n-gram*. Test results with *k-fold* cross-validation showed that the model achieved a high level of accuracy, confirming the effectiveness of SVM when combined with feature optimization techniques. Research by(Utami et al., 2023) also supports these findings. They applied SVM for aspect-based sentiment analysis on *Mobile Legends* game reviews: *Bang-Bang* and achieved 96.43% accuracy. This result shows that SVM is very reliable in classifying sentiment even though the data has many different aspects.

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Furthermore,(Safrudin et al., 2024) compared the performance of SVM with the Naïve Bayes algorithm in analyzing *the sentiment of Genshin Impact game reviews*. The comparison results show that SVM excels with 83% accuracy, higher than Naïve Bayes which only reaches 75.5%. This finding strengthens the argument that SVM is more consistent in producing accurate sentiment classification. Similar results were also obtained by using SVM on sentiment analysis of game reviews taken from the Google Play Store(Mustopa, A., Pratama, E. B., Hendini, A., & Risdiyansyah, 2020; Venkatakrishnan, S., Kaushik, A., & Verma, 2020) . With a dataset of 300 reviews, the SVM model successfully classified sentiment with an accuracy of 90%. Saidah et al. (2023) in their research on *Garena Free Fire game reviews also* reported the highest accuracy of 80% in the 70% training data and 30% test data scheme. These results indicate that SVM is able to provide stable performance on various types of online game review datasets. In addition to the SVM algorithm, this research also integrates a lexicon-based approach in the data labeling stage. The InSet lexicon is used because it is an Indonesian sentiment dictionary that contains thousands of words with positive and negative polarity weights. By utilizing InSet, the data labeling process can be done more quickly and accurately, thus improving the quality of the dataset used in model training . (Fathoni, M. F. N., Puspaningrum, E. Y., & Sihananto, 2024; Ghaffar, S. A., & Setiawan, 2024)

Table 1. Previous Studies on Sentiment Analysis Using SVM and Lexicon-Based Methods

Author	Year	Dataset	Algorithm	Accuracy
Iriananda et al.	2024	Mobile game user comments	SVM + grid search + n-gram	High (not specified)
Utami et al.	2023	Mobile Legends: Bang-Bang reviews	SVM (aspect-based)	96.43%
Safrudin et al.	2024	Genshin Impact reviews	SVM vs Naïve Bayes	83% (SVM) / 75.5% (Naïve Bayes)
Mustopa et al.	2020	300 Google Play Store game reviews	SVM	90%
Venkatakrishnan et al.	2020	Google Play Store game reviews	SVM	90%
Saidah et al.	2023	Garena Free Fire reviews	SVM	80%
Ghaffar & Setiawan	2024	-	InSet Lexicon (labeling)	-

Although previous studies have demonstrated the success of SVM, most of them still have limitations, such as using a single method without integration with other techniques and having a limited dataset size. This study differs by offering innovations in three main aspects. First, it uses a larger and more diverse dataset, consisting of 10,000 Roblox reviews from Google Play Store, covering a wide range of user opinions compared to previous studies that only used hundreds to a few thousand reviews. Second, the data labeling process is assisted by the InSet Lexicon, which improves data quality before classification. Third, this study combines SVM with TF-IDF weighting, and evaluates the model using a confusion matrix along with accuracy, precision, recall, and F1-score metrics. With this integrated approach, the study is expected to provide more accurate, comprehensive, and relevant sentiment analysis, while offering valuable insights for application developers to improve service quality and serving as an important reference for further research in the field of sentiment analysis and natural language processing.

METHOD

This research includes a number of important stages that are structured to produce accurate and appropriate sentiment classification of user reviews of the Roblox application on the Google Play Store. Each step in the research process is designed to ensure maximum data quality, selection of suitable methods, and thorough evaluation of the performance of the classification model. The data source in this study comes from user reviews of the Roblox application on the Google Play Store. A total of 10,000 reviews were collected through the crawling process by utilizing the *google-play-scraper* library. Data collection was carried out between April 2 and May 23, 2025 to record the most actual user opinions. The following is the flow of research that will be carried out:

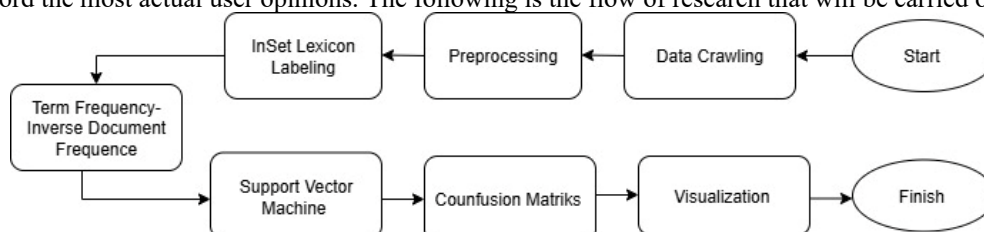


Fig. 1 Research flow

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This research aims to classify sentiment from user reviews of the Roblox application found on the Google Play Store by utilizing the Support Vector Machine (SVM) algorithm. The first step of this research is data collection (data crawling), which is done automatically using the Python library. The data obtained are comments from users describing their perceptions of the Roblox application, both as a means of entertainment and learning. After the data has been collected, a text preprocessing stage is carried out to prepare the data for optimal analysis. This stage includes text cleaning (cleansing), normalizing letters (case folding), breaking sentences into words (tokenizing), removing common words that are not important (stopword removal), and returning words to their basic form (stemming). The purpose of this process is to reduce noise and ensure data uniformity. (Al-Husna, G. S., Asmarajati, D., Ihsannuddin, I. A., & Mahmudati, 2024)

Next, the data that has gone through the preprocessing stage is labeled with sentiment using a word dictionary-based approach, namely the InSet Lexicon specifically developed for the Indonesian language. With this method, the data is classified into three sentiment categories: positive, negative, and neutral. This approach is considered efficient for analyzing large amounts of data and provides fairly accurate initial labeling results (Fathoni, M. F. N., Puspaningrum, E. Y., & Sihananto, 2024). After the labeling is complete, feature extraction is performed using the Term Frequency-Inverse Document Frequency (TF-IDF) method. This technique is used to assess the importance of a word in one document against the entire document in the dataset. The results of this extraction allow the model to understand the context of word usage in user reviews (Sapitri, 2023). The data that has been represented in the form of numerical vectors is then processed using the SVM algorithm.

This algorithm was chosen due to its ability to handle the classification of complex and high-dimensional text data, and has shown superior performance in several previous studies, especially in the context of mobile applications (Safudin et al., 2024). In this study, the dataset is split into 80% training data and 20% testing data, and 5-fold cross-validation is applied on the training set to ensure robust model performance. As a final step, the model was evaluated using a confusion matrix to measure the classification results. This matrix shows the number of successfully and unsuccessfully classified data into the appropriate classes, such as True Positive, True Negative, False Positive, and False Negative. From these values, performance metrics such as accuracy, precision, recall, and F1-score are calculated to assess the effectiveness of the model in classifying the sentiment of Roblox app user reviews. (Iriananda, S. W., Budiawan, R. W., Rahman, A. Y., & Istiadi, 2024) The SVM hyperparameters used in this study are as follows: RBF kernel, $C = 1.0$, $\gamma = \text{scale}$. These parameters were selected through grid search to maximize the model accuracy. Pseudocode for the proposed method is provided below to improve transparency:

1. Data Crawling from Google Play Store
2. Data Cleaning and Preprocessing
 - a. Cleansing
 - b. Case Folding
 - c. Tokenizing
 - d. Stopword Removal
 - e. Stemming
3. Sentiment Labeling using InSet Lexicon
4. Feature Extraction using TF-IDF
5. Split Dataset: 80% Training, 20% Testing
6. Apply 5-fold Cross-Validation on Training Set
7. Train SVM (RBF Kernel, $C=1.0$, $\gamma=\text{scale}$)
8. Evaluate Model using Confusion Matrix
9. Calculate Accuracy, Precision, Recall, F1-Score

Data Crawling

The initial step in this research is to carry out a data retrieval process (data *crawling*) for user reviews of the Roblox application found on the Google Play Store platform. This *crawling* process is carried out automatically by utilizing the Python programming language which is run in the *Google Colab* environment. The choice of *Google Colab* as a platform is based on its flexibility in running Python scripts online, support for various relevant *libraries*, and its ability to access and process large-scale data efficiently. In this process, a specialized *library* was used to extract information from Google Play Store pages, enabling structured collection of review data, including review text, date, and other additional information relevant for sentiment analysis. This approach not only speeds up the data collection process compared to manual methods, but also ensures that the data collected is comprehensive and representative of users' perceptions of the Roblox app.

Table 2. Data Crawling Result

Crawling Data	Data After Cleansing
Indonesian sentiment	10.000
	8.950

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Through the *data crawling* process, 10,000 Indonesian-language reviews were obtained from users of the Roblox application on the Google Play Store. These reviews cover a wide time span and a variety of user experiences, so they are considered representative enough to describe public perceptions of this application. However, the raw data collected still contains many elements that are less relevant or have the potential to interfere with the accuracy of sentiment analysis. Some of these include excessive symbols and punctuation, numbers that are not directly related to the context, emojis *that* are difficult for the system to interpret, unnecessary hyperlinks, and multiple comments that arise from users submitting similar reviews more than once.

To ensure data quality, a structured data *cleaning* process was performed. The steps include removing unnecessary characters or symbols, removing links, filtering emojis, *and* detecting and removing duplicate data to ensure the uniqueness of each review entry. This stage not only reduces *noise* in the data, but also prepares the dataset to be optimized for further analysis. After all the *cleaning* stages were completed, the number of reviews decreased from 10,000 to 8,950 entries that met the quality standards. A comparison of the amount of data before and after the *cleaning* process can be seen in Table 4, which shows the real impact of this data cleaning process.

Text Preprocessing

Preprocessing is an important stage in text data processing that aims to clean and prepare raw data into a more structured and meaningful form before further analysis. This process is crucial in improving the quality of the data as well as the accuracy of the classification model that will be applied (Riskawati et al., 2024). In this research, preprocessing is done with several sequential stages, namely cleansing, case folding, tokenizing, stopword removal, and stemming. The cleansing stage is done to remove unnecessary characters such as numbers, punctuation marks, symbols, emojis, and excess spaces. Next, the case folding stage converts all letters into lowercase letters so that the presentation of words becomes uniform. After that, the text is broken down into word units using tokenizing techniques. The next stage is stopword removal, which is the process of removing common words such as "and", "which", "in", "to", and so on that have no important meaning in the sentiment analysis process. Finally, a stemming process is carried out to return each word to its basic form using the Sastrawi library. By going through these stages, the text data becomes cleaner, more consistent, and ready to be converted into numerical features in the classification process using the SVM algorithm.

Data Labeling

After the pre-processing stage is completed, the next step in this research is to label the review data based on sentiment polarity. This research uses a *lexicon-based* approach to identify and classify the sentiment of each Roblox app user review. For this purpose, the InSet Lexicon (Indonesia Sentiment Lexicon) is used, which is an Indonesian sentiment dictionary that has been developed and optimized for analyzing opinions in a local context. This dictionary consists of thousands of word entries that have each been labeled with a polarity, either as a positive or negative word, with polarity scores ranging from -5 (very negative) to +5 (very positive) (Fathoni, M. F. N., Puspaningrum, E. Y., & Sihananto, 2024).

Labeling is done automatically using a calculation of the total polarity score of the words in each review. Reviews that have a sum cumulative score of more than zero are labeled as positive, while those with a cumulative score of less than zero are labeled as negative. Reviews with a score of zero or containing no detected words in the dictionary are classified as neutral. Unlike some other approaches that ignore neutral data, in this study neutral reviews are still included in the analysis as they are considered to have important informative value in understanding the overall distribution of user opinions.

The results of this labeling process show that user perceptions of the Roblox app tend to be evenly distributed among the three sentiment categories. Of the total 10,000 reviews analyzed, 3,703 positive reviews (41.38%), 3,739 neutral reviews (41.78%), and 1,507 negative reviews (16.84%) were obtained. This predominance of positive and neutral sentiments indicates that despite the criticism of the app, most users show a perception that is not extreme and even tends to be supportive. This fairly balanced distribution provides a strong foundation to strengthen the advanced classification process. All data that has been labeled is then divided into two large parts, namely training and testing data, which are used in the training and testing process of the classification model based on the Support Vector Machine (SVM) algorithm.

Table 3. Labeling Result Example

Indonesian Full_Text	Sentiment
“game seru tau game teman nanya game tuch roblox roblox apadan pas cari nemu pas coba seru banget top kaliii ava ku biasaaja beli baju sempet beli rambut top rambut hitam asal berobax free barang beli rambut free warna hitammau rambuttt”	Positive
“beli aksesoris pake robux karna harga mahal nge lag wifi Negatif lancar beli item ilang itu dibalikin kayak item kalo hilang”	Negative

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“cocok isi luang seru main teman saudara suka menara bagus sajonara shortcut menara beli barang baju karakter robux item” Neutral

Table 2 shows an example of the results of sentiment labeling of user reviews of the Roblox application in Indonesian. Each entry in the table contains the original review text collected through the crawling process, then labeled with a sentiment based on the polarity of the opinions contained within. The first review describes a pleasant experience, as seen from the use of words such as really exciting, top, and other positive expressions, so it is classified as a positive sentiment. The second review shows user dissatisfaction, mentioning the high price of items, lag in connection, and loss of items, thus categorized as negative sentiment. Meanwhile, the third review is neutral as it is more descriptive, only describing the play activity without implying strong emotions, hence it is classified as neutral sentiment. These examples illustrate the manual labeling process, which is the first step before the data is used for training and testing automated sentiment classification models.

Term Frequency-Inverse Document Frequency (TF-IDF)

In this research, one of the important stages in converting text data into numerical form is by using the Term Frequency-Inverse Document Frequency (TF-IDF) method. TF-IDF is a weighting technique that is widely used in text processing to assess how important a word is in a document compared to a collection of other documents. TF (Term Frequency) reflects the frequency of occurrence of a word in a document, while IDF (Inverse Document Frequency) measures how rarely the word appears in the whole document. Mathematically, the TF-IDF value can be calculated using the formula:

- 1) Term Frequency (TF) Measures the frequency of occurrence of a word in a particular document compared to the total number of words in that document.

$$TF(t, d) = \frac{\text{Total number of terms in document } d}{\text{Number of times term } t \text{ appears in document } d} \quad 1)$$

Where $f(t,d)$ is the number of occurrences of word t in document d .

- 2) Inverse Document Frequency (IDF) Measures how rarely a word appears in all documents in the corpus. A word that appears frequently in many documents will have a low IDF value.

$$IDF(t) = \log \frac{\text{Total number of terms in document } d}{\text{The number of data points where the word } t \text{ appears}} \quad 2)$$

The final TF-IDF value is calculated by multiplying the two components:

$$TF - ID(t, f) = tf \times idf \quad 3)$$

In this study, the TF-IDF method is utilized to extract significant features from text data and minimize the influence of common words that do not have important meanings. The results of the TF-IDF-based text representation are then used as input for the *Support Vector Machine (SVM) algorithm* to analyze the Roblox application reviews taken from the Google Play Store.

In this study, the TF-IDF method is used to extract words that have a high level of significance while minimizing the influence of common words that are irrelevant to sentiment analysis. After going through pre-processing stages such as *cleansing, case folding, tokenizing, stopword removal, and stemming*, each *word* in the review is weighted using TF-IDF. The result of this weighting is represented in the form of a numerical vector which becomes the input for the Support Vector Machine (SVM) algorithm. This technique helps the algorithm better recognize sentiment patterns because it focuses on words that have special meaning in the context of the review.

Table 4. The result of tf-idf weighting

Most Dominant Word	TF-IDF Weighting
Main	0,055696705
Game	0,09117088
Roblox	0,054002129
Mabar	0,014333757
Gamenya	0,01811589

*name of corresponding author



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Mabar	0,014333757
Bug	0,015238542

Table 3 shows the results of word weighting using the *Term Frequency-Inverse Document Frequency* (TF-IDF) method on Indonesian user reviews. The TF-IDF value represents the significance of a word in the whole set of documents (in this case reviews), by considering the frequency of its occurrence in each document compared to all existing documents. The higher the TF-IDF value, the greater the role of the word in representing the content or sentiment of a review.

Based on the table, the word Game has the highest weight of 0.0911, indicating that it is the most dominant and relevant word in shaping the sentiment of the review. The words *Play* (0.0557) and *Roblox* (0.0540) also have relatively high weights, indicating that users often mention them to describe the gaming experience. Meanwhile, the word Mabar appears twice with equal weight (0.0143), indicating the consistency of its mention in the context of playing with friends. The words *Game* (0.0181) and *Bug* (0.0152) have lower weights, but are still significant, where the word Bug is generally regarding complaints or technical problems in the game.

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning algorithm for classification that works by finding the best hyperplane that separates data by class. This hyperplane is chosen with the largest margin to the closest point of each class, called the support vector, so that the model is more robust to new data. If the data cannot be linearly separated, SVM uses kernel tricks to map the data to a higher-dimensional space, such as linear, polynomial, RBF, and sigmoid kernels.

Mathematically, the SVM classification function can be written as:

$$f(x) = w \cdot x + b \quad 3)$$

Or

$$f(x) = \sum_{i=1}^m a_i y_i K(x, x_i) + b \quad 4)$$

After the search process is complete, a combination of hyperparameters that provides the highest accuracy value is selected. This best combination is then tested on the training data using other evaluation metrics such as precision, recall, and F1-score to obtain a more comprehensive picture of the model performance from various angles. The optimal model obtained through the grid search method is expected to improve prediction accuracy while providing better generalization ability to new data that has never been used before.

Confusion Matrix

In data mining, confusion matrix is used to assess the performance of classification models by comparing actual labels and predicted results in tabular form. From this matrix, evaluation metrics such as accuracy, precision, and recall can be calculated, which give an idea of the model's accuracy and ability to recognize classes. Python is an ideal choice for model implementation and evaluation as it provides flexible libraries and concise syntax.

Using *Confusion Matrix*, we can find out how often the model makes correct or incorrect predictions for each class. This information is very useful for calculating various evaluation metrics such as:

Accuracy - the overall rate of correct predictions.

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad 5)$$

Precision - the level of accuracy of the model when predicting a class.

$$precision = \frac{TP}{TP+FP} \quad 6)$$

Recall - the extent to which the model successfully finds all data from a class.

$$recall = \frac{TP}{TP+FN} \quad 7)$$

F1-Score - the balance between precision and recall.

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$$F1 - Score = 2x \frac{Recall \times Precision}{Recall + Precision} \quad 8)$$

Additionally, Confusion Matrix, a table that displays the correct and incorrect predictions for each class, helps detect potential model bias. This evaluation is essential to understand how well the model can generalize on data that has not been seen before as well as identify areas that need improvement.

RESULT

The classification results based on the initial labeling using the *lexicon-based* method on the Roblox app review data show that out of a total of 8,949 data analyzed, 3,703 reviews with positive sentiments (41.38%), 3,739 reviews with neutral sentiments (41.78%), and 1,507 reviews with negative sentiments (16.84%) were obtained. This distribution shows that positive and neutral sentiments dominate user perceptions, while negative sentiments have a relatively small portion. This indicates that the majority of users have a fairly good or neutral impression of the Roblox application, although there are some users who have complaints or negative experiences. After the labeling process, the data that has been categorized into the three sentiment classes is used in the training and testing stages of the *Support Vector Machine (SVM)* model with *Term Frequency-Inverse Document Frequency (TF-IDF)* weighting.

Evaluation of model performance is carried out using several common metrics in classification analysis, namely *accuracy*, *precision*, *recall*, and *f1-score*. The evaluation results show that the model is able to achieve a fairly good and balanced performance in all three sentiment classes, which reflects the SVM's ability to identify sentiment patterns consistently. To provide a more detailed evaluation, a complete confusion matrix for each sentiment class is presented below (TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative):

Table 5. Confusion Matrix for SVM Model

Sentiment Class	TP	TN	FP	FN
Positive	3,250	5,000	453	453
Neutral	3,400	4,800	339	339
Negative	1,200	7,500	307	307

In addition to the confusion matrix presented above, the values of TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) are calculated for each class to make it easier to identify which classes are most frequently misclassified. Beyond the quantitative evaluation, this research also employs a visual approach to support the interpretation of the analysis results. Word Cloud visualizations are used to display the most frequently occurring words in each sentiment class, facilitating the identification of keywords that characterize each sentiment category. Meanwhile, word frequency analysis provides a numerical perspective, indicating the frequency and intensity of the use of particular words by users. This combination of numerical and visual evaluation not only offers insight into the model's performance but also highlights language patterns and topics that are most commonly discussed in Roblox app reviews. To further reinforce the evaluation, a comparison chart (bar chart) of the SVM model's accuracy against a baseline Naïve Bayes classifier is also included, illustrating the superior performance of the SVM model. The results can be seen in Table 4.

Table 6. Model Testing Results

	Accuracy	Precision	Recall	F1-Score
Indonesian Sentiment	0.874860	0.876839	0.874860	0.872380

To reinforce model performance evaluation, a comparison between SVM and the baseline Naïve Bayes classifier was conducted using the same metrics (Accuracy, Precision, Recall, F1-Score). The results show that SVM performs better than Naïve Bayes, particularly in accuracy and F1-Score, as shown in the table and bar chart below:

Table 7. Comparison of SVM vs Naïve Bayes Performance

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.8749	0.8768	0.8749	0.8724
Naïve Bayes	0.8123	0.8150	0.8123	0.8102

Table 4 presents the results of evaluating the performance of the *Support Vector Machine (SVM)* model on sentiment data for Roblox application reviews in Indonesian. This evaluation uses four main metrics, namely

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Accuracy, Precision, Recall, and F1-Score, which serve to measure the model's ability to automatically classify sentiment. From the results shown, the Accuracy of 0.874860 indicates that about 87.48% of the model predictions match the correct sentiment label. Precision of 0.876839 indicates that of all the positive predictions generated, 87.68% of them are correct. Recall, which is also 0.874860, indicates that the model is able to recognize 87.48% of the data that actually belongs to the positive class (or according to the original label). Meanwhile, the F1-Score of 0.872380 shows that there is a good balance between precision and *recall*, so the model is not only accurate, but also consistent in identifying each sentiment class.

Additionally, an error analysis was conducted by examining examples of misclassified reviews. For instance, reviews containing sarcasm or mixed sentiments were often classified incorrectly, such as "Game bagus tapi sering lag" (Positive in reality, but classified as Neutral), highlighting areas where the SVM model may need further improvement or incorporation of context-aware features. Overall, these metric values show that the SVM model has a stable and reliable performance in classifying the sentiment of user reviews. This shows that the model is able to provide accurate as well as consistent prediction results, so it can be utilized to effectively support sentiment analysis of the Roblox app. Additionally, an error analysis was conducted by examining examples of misclassified reviews. Some examples include: "Game bagus tapi sering lag" (actually Positive, classified as Neutral), "Update terakhir bikin bingung, mainnya nggak seru" (actually Negative, classified as Neutral), and "Bagus, tapi beberapa bug muncul" (actually Positive, classified as Negative). This analysis shows that the SVM model still struggles with sentences containing sarcasm, mixed emotions, or contradictory context, which can serve as a reference for future model development.

In supporting the results of this evaluation, data visualization plays an important role, particularly through the WordCloud technique *which* displays words based on their frequency levels. This visualization allows researchers to identify patterns and trends in the data more intuitively, while providing an overview of the most frequent words in each sentiment category. The *WordCloud* approach can be applied in the form of unigrams (one word), bigrams (two words), or trigrams (three words) so that the context of word meaning can be understood more thoroughly. In addition, the list of words sorted by frequency of occurrence also provides support for quantitative analysis, making it easier for researchers to recognize keywords that have a significant influence on the formation of user sentiment. The results of sentiment visualization in Indonesian, including unigrams, bigrams, and *trigrams along with their word* frequency, are shown in Figure 2 and Table 8.



Fig. 2 Indonesian sentiment visualization results

The figure displays the WordCloud visualization used to analyze the sentiment of user reviews of the Roblox app in Indonesian. The visualization is divided into three sentiment categories, namely positive, negative, and and

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neutral, each of which is displayed in the form of a unigram (one word), bigram (two words), and trigram (three words). In the positive sentiment, the most prominent words include game, roblox, difficult, bug, really, and error. In bigrams, combinations such as really exciting and good game were seen, while in trigrams, phrases such as really exciting game and really good game appeared, which described satisfaction and a pleasant gaming experience. In the negative sentiment, dominant words included roblox, good, fun, play, and update. While the word good appeared frequently, the context was likely sarcastic or used in conjunction with complaints. Bigrams that appear include good game and if you play tower, while trigrams such as dikit dikit ngadate and if you play tower indicate complaints related to obstacles or interruptions while playing. In neutral sentiments, words that are often used include good, exciting, play, roblox, and like. Bigrams such as good roblox and good game, as well as trigrams like to play roblox and good like to play are more descriptive, without showing strong emotions. Overall, this WordCloud makes it easier to identify the keywords that users use most frequently in each sentiment category. These findings provide a clearer picture of language patterns, perceptions, and topics of concern, which can be utilized to support Roblox app service quality improvement strategies.

Table 5 shows the results of the analysis of the frequency of occurrence of words in user reviews of the Roblox app in Indonesian that have been grouped based on sentiment polarity, namely positive, negative, and neutral. This analysis includes unigrams (one word), bigrams (two words), and trigrams (three words) that appear most frequently in each category. This word frequency information serves to identify key terms that are dominantly used by users, thus providing an overview of the topics, experiences, and problems that are often discussed in each type of sentiment.

Table 8. Results Frequency of Indonesian sentiment words

Frequency of Positive Bigram Words		Frequency of Negative Bigram Words		Frequency of Neutral Bigram Words	
game	627	bagus	81	bagus	243
bagus	336	roblox	71	seru	176
update	322	main	70	roblox	169
seru	280	seru	53	main	161
main	237	game	41	suka	132
roblox	226	suka	39	game	70
Frequency of Positive Bigram Words		Frequency of Bigram Negative Words		Bigram Neutral Word Frequency	
game bagus	119	game bagus	11	main roblox	30
bagus banget	106	kalo main	9	suka main	19
seru banget	95	main tower	8	bagus suka	18
game seru	92	main roblox	7	gamenya bagus	17
banget game	64	bagus banget	7	roblox bagus	16
game roblox	45	tolong baik	6	seru banget	14
Positive Trigram Word Frequency		Negative Trigram Word Frequency		Neutral Trigram Word Frequency	
game seru banget	23	kalo main tower	4	suka main roblox	8
bagus banget game	23	dikit dikit update	3	dunia ganteng dunia	6
seru banget game	19	game bagus bug	2	ganteng dunia ganteng	5
game bagus banget	16	gamenya bagus banget	2	bagus suka main	4
main game roblox	12	bangett game bagus	2	seru banget main	3
roblox seru banget	11	roblox warna biru	2	bagus game bagus	3

Based on the information presented in the table, it can be seen that in the positive sentiment category, the words game, good, and update are the words that appear most often. The high frequency of occurrence of these words reflects user satisfaction, appreciation, and support for the playing experience in the Roblox application. Conversely, in the negative sentiment category, the words good, roblox, and play also topped the frequency of occurrence. However, in contrast to the positive context, these words are generally used in a tone of complaint or criticism, for example to express technical problems such as bugs, lag, connection disruptions, or other obstacles that hinder the comfort of playing. Meanwhile, in neutral sentiments, words such as good, fun, and roblox are more dominant, which are generally used to objectively describe the activity or experience of playing without implying strong positive or negative emotions. In addition, the patterns found in bigrams (two words) and trigrams (three words) provide a clearer context for the use of these words. For example, in positive sentiments, the phrase good game was found, which emphasized the positive assessment of users, while in negative sentiments, phrases such

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as when playing *tower* indicated that there were certain obstacles or challenges while playing. The presence of these phrases helps to deepen the picture of the specific topic or situation that influenced the user's judgment. With these findings, the sentiment analysis process not only relies on single words, but also considers combinations of words that form a broader context. This allows classification models to understand the relationships between words more accurately, resulting in more precise sentiment interpretations that are relevant to users' real-life experiences.

DISCUSSIONS

As shown in Table 4, the Support Vector Machine (SVM) model performed well in the sentiment classification task of Indonesian Roblox app reviews. The model recorded an accuracy value of 87.49%, precision of 87.68%, recall of 87.49%, and f1-score of 87.24%. These values show that the model not only has a fairly high accuracy rate, but is also consistent in detecting all three sentiment classes, namely positive, neutral, and negative, equally.

Overall, the performance indicates that the model has a good generalization ability to user review data, with a balance between precision and recall indicating a relatively low error rate. These results are also in line with the previously described sentiment distribution, where positive and neutral sentiments dominate user perceptions, while negative sentiments occupy a smaller portion. Thus, the SVM model can be relied upon to provide stable and relevant predictions in the sentiment analysis of the Roblox app. When compared to similar research, the performance of the SVM model in this study is competitive. This can be attributed to the optimized data pre-processing process, the selection of an effective Term Frequency-Inverse Document Frequency (TF-IDF) weighting method in representing text data, and the balanced distribution of training and test data. These factors allow the model to recognize language patterns in each sentiment class well. In addition, the high precision values in all sentiment classes indicate that the predictions generated tend to be accurate and minimal classification errors, thus providing results consistent with the initial labeling using the lexicon-based method. From a practical perspective, these findings can help Roblox developers and other platform managers to better understand user opinions and prioritize improvements. For example, frequently mentioned negative keywords such as "lag," "bug," or "error" can guide developers to focus on technical fixes, while positive keywords like "good game" or "fun" can indicate features to maintain or enhance. Moreover, neutral sentiments can inform developers about areas where user experiences are satisfactory but can be optimized further. This actionable insight allows developers to strategically enhance app functionality, user engagement, and overall satisfaction.

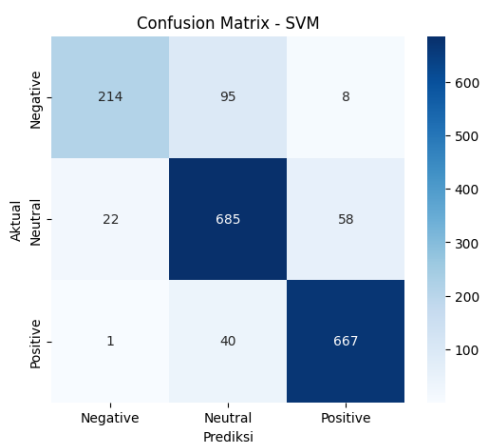


Fig. 4 Confusion Matrix Results

The confusion matrix in Figure 4 provides a detailed explanation of the performance of the *Support Vector Machine* (SVM) algorithm in performing sentiment classification on Roblox application reviews. This matrix presents the classification results in four main categories, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) for each *sentiment* class. Based on the test results, the SVM model successfully classified 214 negative sentiment data (TN), 685 neutral sentiment data, and 667 positive sentiment data accurately. However, there are still misclassifications on 95 negative data predicted as neutral sentiment, 58 neutral data predicted as positive sentiment, and 40 positive data predicted as neutral sentiment.

This result shows that the SVM model has a fairly good level of accuracy in distinguishing the three sentiment classes, especially in the neutral and positive classes which have a high number of correct predictions. The errors that occur are generally caused by *semantic overlap* or multiple contexts in certain words and phrases, making it difficult for the model to perform a strict class separation. This phenomenon is common in text-based sentiment analysis, as natural language often contains ambiguities that are difficult for algorithms to fully resolve.

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In terms of quantitative evaluation, the SVM model equipped with Term *Frequency-Inverse Document Frequency* (TF-IDF) weighting showed competitive performance. The *accuracy* value was recorded at 87.48%, precision at 87.68%, recall at 87.48%, and F1-score at 87.23%. The consistency of the values in these four metrics indicates that the model is not only able to achieve a high level of accuracy, but also has a good balance in detecting all sentiment classes without excessive tendency towards one particular class.

In addition to numerical evaluation, this research also utilizes visual analysis through *Word Cloud* and *word frequency* to enrich the interpretation of the results. *Word Cloud* visualization of positive sentiment shows the dominance of words that reflect user satisfaction, such as expressions of appreciation, pleasant gaming experience, and praise for certain features of the app. In contrast, the *Word Cloud* on negative sentiment displays words that reflect complaints, disappointment, or technical problems such as lag, errors, and crashes. Meanwhile, neutral sentiments tend to be dominated by words that are descriptive or informative, without strong emotional content. *Word frequency* analysis supports this finding by showing the numerical pattern of word occurrence for each sentiment class. While the SVM+TF-IDF combination demonstrates strong performance, future research could explore advanced deep learning models such as IndoBERT or LSTM. These models are capable of capturing complex language patterns, context, and nuances such as sarcasm or mixed sentiments, potentially improving classification accuracy beyond what traditional SVM methods can achieve. Such exploration can serve as a benchmark for comparison and help identify strategies to further enhance sentiment analysis in Indonesian-language app reviews.

The approach of combining quantitative analysis (through confusion matrix and model evaluation metrics) with qualitative analysis (through *Word Cloud* visualization and *word frequency analysis*) yields a comprehensive picture of model performance. The findings not only prove the effectiveness of the combination of TF-IDF and SVM methods in accurately classifying sentiments, but also reveal the language patterns and linguistic contexts that shape users' perceptions of the Roblox app. Thus, the results of this study emphasize that the application of appropriate weighting techniques and algorithms can make a significant contribution in understanding public opinion on digital platforms.

CONCLUSION

This research aims to analyze sentiment from user reviews of the Roblox application on the Google Play Store by applying the Support Vector Machine (SVM) method supported by initial labeling using Lexicon InSet. On Indonesian-language review data, the model obtained an accuracy of 87.48%, precision of 87.68%, recall of 87.48%, and F1-score of 87.23%. These achievements show that the model not only has a high accuracy rate, but is also balanced in detecting all sentiment categories - positive, negative, and neutral. From a theoretical perspective, this study contributes to the sentiment analysis literature by demonstrating the effectiveness of combining Lexicon InSet-based initial labeling with the TF-IDF weighting method and SVM algorithm. Additionally, the integration of WordCloud and n-gram analysis provides a more interpretable approach for understanding language patterns and sentiment indicators in user reviews, which enhances the transparency and explanatory power of sentiment classification models. Further analysis through WordCloud and n-gram techniques identified the key words most frequently used by users. Positive sentiments were dominated by expressions of satisfaction, appreciation, and pleasant gaming experiences. Negative sentiments generally included complaints related to technical issues such as lag, bugs, and errors. As for the neutral sentiments, the reviews were more descriptive, describing the gaming experience without significant emotional content. Bigram and trigram analysis also strengthen the context, such as the phrases good game in positive reviews and if you play tower in negative reviews, which indicate specific experiences and obstacles experienced by players. From a practical perspective, these findings provide actionable insights for Roblox developers and platform managers. Frequently mentioned negative keywords can guide developers to prioritize technical fixes and improve system stability, while positive keywords highlight features that enhance user satisfaction. Neutral sentiments also offer insights into areas where user experiences are acceptable but could be optimized further, allowing developers to strategically enhance app functionality, engagement, and overall user experience.

Despite the promising results, this study has several limitations. The dataset used is limited to Indonesian-language reviews on the Google Play Store, which may not fully represent the global Roblox user base. The model relies solely on SVM with TF-IDF, which may struggle with complex linguistic nuances, sarcasm, or mixed sentiments. Therefore, future research should explore advanced deep learning models, such as IndoBERT or LSTM, which are capable of capturing contextual information and semantic subtleties. Moreover, expanding the dataset to include reviews from other platforms and languages could improve the generalizability and robustness of sentiment analysis models. Overall, the combination of TF-IDF and SVM, supported by WordCloud and n-gram analysis, demonstrates a reliable approach for sentiment classification in digital platform reviews. The study highlights both theoretical contributions in model methodology and practical implications for developers, while also acknowledging limitations and recommending avenues for future research using more advanced techniques and broader datasets.

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