Sistemasi: Jurnal Sistem Informasi
Volume 13, Nomor 6, 2024: 2767-2779
ISSN:2302-8149
e-ISSN:2540-9719

Comparison of Naive Bayes and SVM Algorithms for Sentiment Analysis of PUBG Mobile on Google Play Store

[1]Putri Ratna Sari, [2] Dwi Rosa Indah*, [3]Errissya Rasywir, [4]Mgs. Afriyan Firdaus, [5]Ghita Athalina
[1,2,4,5]Sistem Informasi, Fakultas Ilmu Komputer, Universitas Sriwijaya
[3]Fakultas Ilmu Komputer, Universitas Dinamika Bangsa Jambi
[1,2,4,5]Jl. Raya Palembang - Prabumulih No. KM. 32, Indralaya
[3]Jl. Jendral Sudirman, Thehok, Jambi
*e-mail: *indah812@unsri.ac.id*

(***received***: 15 November 2024, ***revised***: 22 November 2024, ***accepted***: 23 November 2024)

Abstract
PlayerUnknown's Battlegrounds (PUBG) Mobile is one of the most popular mobile games in Indonesia, according to data from the Google Play Store. According to the Google Play Store, the game has a rating of 3.8 with 49.5 million reviews. While a considerable number of users express satisfaction, a significant proportion of reviews also contain criticism regarding the gameplay and features. However, a cursory examination of reviews may not fully capture the nuances of user sentiment, necessitating a more comprehensive sentiment analysis. This research will employ a positive and negative sentiment analysis of Indonesian PUBG Mobile reviews on the Google Play Store, utilizing a comparative approach to evaluate the performance of two algorithms: Naïve Bayes and Support Vector Machine (SVM). The data set comprised 2,000 user reviews, which were collected using a scraping technique. Following this, a labeling process was conducted based on the rating, data were preprocessed, TF-IDF weighting was applied, and both algorithms were implemented. The findings indicated that users expressed satisfaction with the game's visuals and gameplay. However, there were also technical concerns that required attention, including bugs, server instability, lag, and performance issues. The SVM algorithm demonstrated superior performance, with an accuracy rate of 70.95%, compared to Naïve Bayes, which reached 69.83%. Despite Naïve Bayes's faster processing speed, SVM exhibited greater precision, recall, and F1-score.

Keywords : comparison, naïve bayes, PUBG mobile, sentiment analysis, support vector machine

1 Introduction

The pace of technological advancement is accelerating rapidly in the contemporary global context, with little to no regulatory oversight. The impact of this progress is evident in a multitude of domains, including the education sector, the economy, health services, and other areas [1]. Furthermore, human creativity is developing at a rapid pace, resulting in a multitude of novel technological innovations within the domain of entertainment. One such innovation is online gaming [2]. PUBG Mobile (PlayerUnknown's Battlegrounds) is among the most prevalent online games in Indonesia. Developed by Tencent, the mobile iteration of this combat game has ascended to the pinnacle of popularity as the most sought-after game application on the Google Play Store [3].

A review of the Google Play Store reveals that PUBG Mobile has received a rating of 3.8 based on 49.5 million reviews. The rating and review feature is an essential tool for potential users in evaluating the quality of the application based on previous user experience [4]. While the majority of users express satisfaction, there are also criticisms related to the gameplay and features available [5]. However, a simplistic interpretation of positive or negative sentiments from reviews does not always reflect accurate trends, necessitating a more comprehensive and systematic sentiment analysis [6].

Sentiment analysis represents a fundamental aspect of text mining, which is the process of extracting information from unstructured text through the application of algorithms and language analysis techniques [7]. Sentiment analysis is a valuable tool for evaluating the quality of an application by analyzing user feedback. This allows developers to identify the strengths, weaknesses, and areas for improvement of the application [8]. Research has demonstrated the importance of sentiment analysis in user reviews. Positive reviews indicate increased trust and use of the app, while negative reviews can

 ISSN:2302-8149
e-ISSN:2540-9719

negatively impact the company's reputation and indicate customer dissatisfaction that requires immediate attention [9].

Previous studies have employed machine learning techniques for sentiment analysis of application reviews on the Google Play Store. A study conducted on Stumble Guys game reviews using the Naïve Bayes algorithm achieved an accuracy rate of 86% based on an analysis of 1,500 reviews [10]. Meanwhile, the implementation of the Support Vector Machine (SVM) method in the sentiment analysis study of the Digital Korlantas Polri application with 1,200 reviews demonstrated favorable performance, with an accuracy rate of 82% at a data ratio of 90:10 [11]. Both studies indicated that both Naïve Bayes and SVM possess effective capabilities in sentiment classification.

The objective of this research is to examine the positive and negative sentiments expressed in PUBG Mobile reviews on the Google Play Store in Indonesia and to evaluate the performance of two classification algorithms, namely the Naive Bayes algorithm and the Support Vector Machine (SVM). The Naive Bayes algorithm was selected due to its efficiency and speed in data processing, while the SVM algorithm was chosen due to its reliability in processing data with complex and non-linear characteristics. The results of this study are expected to determine which algorithm provides superior accuracy in analyzing user sentiment, thus contributing to the development of a more precise and efficient sentiment analysis system. Furthermore, the findings from this sentiment analysis can provide valuable input for PUBG Mobile developers in an effort to enhance the quality of the game in accordance with the feedback from Indonesian users.

2 Literature Review

Sentiment analysis is a valuable method for gauging player sentiment regarding mobile games, such as PUBG Mobile. A number of researchers have conducted sentiment analysis on the PUBG Mobile game. One such study analyzed six million user reviews of PUBG Mobile, identifying the game's graphical strength and noting the need for improvements in server performance, cheating prevention, and device compatibility [12]. However, the study did not include specific analysis for Indonesian-language reviews, which have their own characteristics and present unique challenges in natural language processing. Other studies have employed the Naïve Bayes algorithm. Through web scraping techniques, researchers collected 1,000 Indonesian reviews, and after the cleaning process, only 810 reviews were used. The results demonstrated that 71% of the reviews exhibited positive sentiments, with an accuracy rate of 83.95% [13].

Although the Naive Bayes algorithm demonstrates satisfactory performance, some studies have compared it with other algorithms, such as the Support Vector Machine (SVM), with the objective of gaining a deeper understanding. In a study comparing the two algorithms for the purpose of analyzing reviews of the video game Clash of Clans, it was found that the SVM algorithm yielded more optimal results with a 93% accuracy rate, while the Naive Bayes algorithm achieved a 91.6% accuracy rate [14]. Another study indicated that the SVM algorithm exhibited superior performance in the sentiment classification task of Indonesian language reviews on the Google Play Store platform, with an accuracy rate of 81.46% compared to the Naive Bayes algorithm, which only reached 75.41% [15].

Furthermore, a study comparing the efficacy of algorithms in the sentiment analysis of Twitter data pertaining to Regional Head Elections (PILKADA) revealed that the Naïve Bayes Classifier (NBC) exhibited superior performance in terms of accuracy and recall, at 81.7%, in comparison to SVM, which attained 80.7%. Nevertheless, SVM demonstrated superior precision, with an 84% accuracy rate compared to NBC's 80% [16]. Moreover, the study concentrated on examining the sentiment of Twitter users regarding the Peduli Lindungi application. The findings revealed that SVM and Naïve Bayes exhibited a nearly identical accuracy rate, with SVM marginally superior at 86% compared to Naive Bayes, which attained 85% using the k-fold test method. However, Naïve Bayes demonstrated a distinct advantage in terms of processing speed [17].

A review of the literature reveals that sentiment analysis research conducted using the Naïve Bayes and Support Vector Machine (SVM) algorithms yields disparate results contingent on the context and dataset employed. In terms of performance, SVM tends to demonstrate superior accuracy, whereas Naïve Bayes exhibits an advantage in data processing speed. However, there is a dearth of research that specifically compares the performance of the Naive Bayes and Support Vector Machine (SVM) algorithms in analyzing the sentiment of user reviews on the PUBG Mobile game in Indonesia.

 ISSN:2302-8149
e-ISSN:2540-9719

Additionally, sentiment research related to previous PUBG Mobile user responses is also still limited to a relatively small amount of data.

This research addresses the aforementioned gap in the literature by conducting a comparative analysis of the Naïve Bayes and Support Vector Machine (SVM) algorithms in terms of accuracy and processing speed, utilising a larger dataset. Furthermore, the characteristics of positive and negative reviews will be analysed through word cloud visualisation, thereby providing comprehensive insights for PUBG Mobile developers.

3 Research Method

The research methods employed included systematic steps that served as a guide or work plan, facilitating the achievement of the desired results. All stages of the research were conducted using Google Collaboratory, a cloud-based platform for executing Python code in a browser, obviating the necessity for local computer software installation. The stages of this research are illustrated in Figure 1.

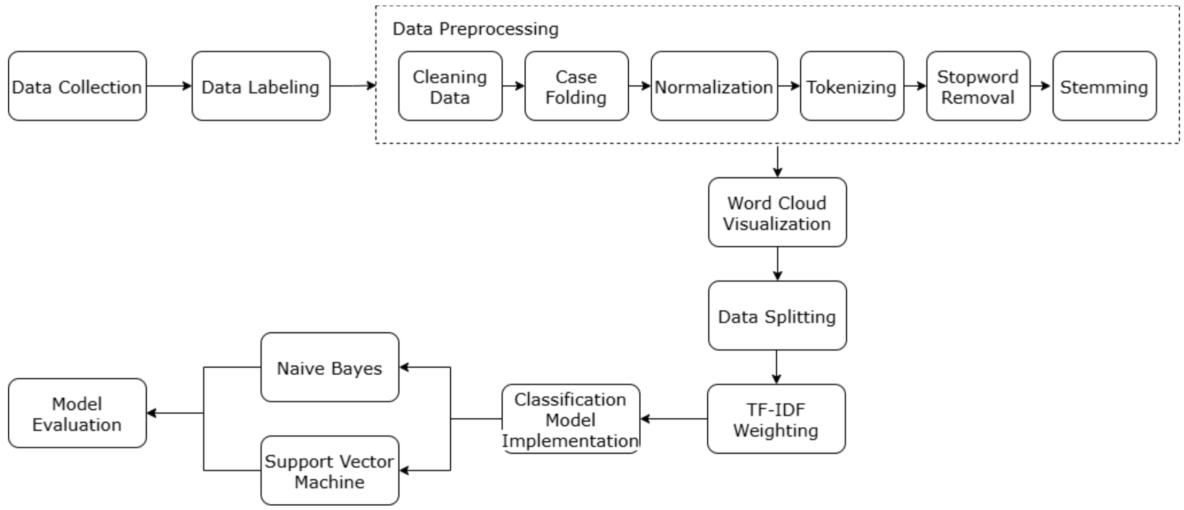

Figure 1. Research stages

3.1 Data Collection

In the data collection stage, the scraping technique is employed to transform data on irregular websites into structured information, thus facilitating further analysis [18]. The scraping technique will employ the `google_play_scraper` library to extract review data from the Google Play Store. The data retrieved includes the text of the reviews and the assigned ratings. The `reviews` function is invoked with the application ID `com.tencent.ig`, which is set to retrieve reviews in Indonesian from PUBG Mobile users in Indonesia. The retrieved reviews are sorted in descending chronological order, with a total of 2000 reviews. Furthermore, the `filter_score_with` parameter is set to None, indicating that all reviews with a rating of 1 to 5 will be retrieved without filtering by a specific score.

3.2 Data Labeling

Sentiment labeling will be conducted based on the ratings provided by users in PUBG Mobile app reviews. Reviews with a rating of < 3 are classified as negative, indicating a negative user experience. Conversely, reviews with a rating of > 3 are classified as positive, indicating a positive user experience. Reviews with a rating of 3 are considered neutral and will be excluded from the dataset, as they lack sufficient clarity to indicate user experience [19].

3.3 Data Preprocessing

The data will be subjected to cleaning and preprocessing in order to prepare it for further analysis. The structure of the data, which is often disorganized, can hinder the processing of the data set as a whole [20]. This process comprises a series of procedures, including data cleaning, the removal of punctuation and superfluous characters, with the objective of elucidating the intended meaning of the sentence [21]. The process of case folding involves converting each text character to lowercase in order to create uniformity [22]. Normalization is the process of aligning words with the standard provisions

ISSN:2302-8149
e-ISSN:2540-9719

of the Indonesian language [23]. In the normalization stage, data from Kaggle.com, which contains a standard Indonesian language dictionary, will be used. Tokenization, the separation of text into individual words, will facilitate analysis [24]. Stopword removal, the elimination of words that do not contribute important meanings, will also be conducted [25]. Finally, stemming, the removal of affixes to obtain the base word and the filtering out of inappropriate words from sentences, will be performed [26]. After preprocessing, data with null values will be removed to maintain the quality of the dataset.

3.4 Word Cloud Visualization

This research employs word cloud visualization to analyze the sentiment and characteristics of words used in user reviews. Word clouds present words in different dimensions based on their number of occurrences, with more dominant words displayed in larger sizes [27]. This visualization facilitates the identification of key topics in the positive and negative sentiments of PUBG Mobile users, and the results are used to provide recommendations to developers.

3.5 Data Splitting

The process of data splitting will result in the division of the PUBG Mobile app user review dataset into two distinct parts: training data and testing data. In order to facilitate this, the `sklearn` library will be employed to perform the splitting of the dataset, utilising the `steming_data` column as the feature and the `label` column as the target. This process will be conducted in a proportion of 80:20, ensuring that each model is trained and tested on a sufficient quantity of data.

3.6 Term Frequency-Inverse Document Frequency Weighting

Subsequently, the TF-IDF method is employed to transform the textual data into a numerical vector representation [28]. The Term Frequency (TF) calculation quantifies the frequency of occurrence of a given word within a document, whereas the Inverse Document Frequency (IDF) measurement assesses the relative scarcity of a word across the entire corpus [29]. To derive the TF-IDF values, a sequence of calculations is necessary, which includes the application of equations (1) to (5):

- Term Frequency (TF)

$$TF_{(t_i,k_j)} = \frac{\sum_{i=1}^{n} f(t_i,k_j)}{n} \quad (1)$$

- Document Frequency (DF)

$$TF_{(t_i,k_j)} = \frac{\sum_{i=1}^{n} f(t_i,k_j)}{n} \quad (2)$$

In this context, DF represents the number of comments containing the t-th term.

- Inverse Document Frequency (IDF)

$$IDF(t_i) = 1n\left(\frac{m+1}{1+DF(t_i)}\right) + 1 \quad (3)$$

- Term Frequency-Inverse Document Frequency (TF-IDF)

$$v_{(t,k)} = TF_{(t,k)} \times IDF_{(t)} \quad (4)$$

Where $v_{(t,k)}$ is the TF weight value associated with IDF.

- TF-IDF weight normalization

$$v_{norm_{(t,k)}} = \frac{v_{(t,k)}}{\sqrt{v_{(1,k)}^2 + v_{(2,k)}^2 + \cdots + v_{(n,k)}^2}} \quad (5)$$

Where $norm_{(t,k)}$ refers to the normalization value for each term.

In this context, the variable "k" refers to the comment itself, while "m" represents the total number of comments analyzed. The variable j indicates the index of each comment, which has a value from 1 to m. The variable t or term includes the terms or words found in the comment, and n is the total number of terms in comment k. The index i is used to identify a particular term in the term list, which also has a value from 1 to m. Finally, f indicates the frequency of the i-th term appearing in the j-th comment.

3.7 Classification Model Implementation

Once the dataset has been prepared, the selected classification algorithms, namely the Naive Bayes and Support Vector Machine (SVM) algorithms, are implemented.

A) Naive Bayes is a probability-based classification algorithm that estimates the independence between conditions [30]. Its accuracy is determined by calculating the positive and negative probabilities, and the sentiment is identified based on the category with the highest probability [31]. The general equation for the Naive Bayes algorithm is represented by Formula (6).

ISSN:2302-8149
e-ISSN:2540-9719

$$P(H|X) = \frac{P(X|H) \times P(H)}{P(X)} \quad (6)$$

In this context, the letter H is used to symbolize hypothetical data within a given class, while X signifies unclassified data. The probability of H is represented by P(H), the probability of X is indicated by P(X), the probability of a hypothesis with a specific condition is denoted as P(H|X), and P(X|H) represents the probability based on the hypothesis condition.

B) A support vector machine (SVM) is a supervised learning algorithm that performs two-class classification in a high-dimensional space by utilizing the optimal hyperplane [32]. SVM employs kernel functions to transform non-linear problems into a linearly separable form, where a variety of kernels are available [33]. The equation for the SVM algorithm is provided in Formula (7).

$$f(x) = w^T x + b \quad (7)$$

In this context, the function f(x) represents the decision-making process that maps the feature vector x into a specific category. The weight vector w is employed to assign relative importance to each feature, while b serves as a bias to adjust the decision hyperplane.

3.8 Model Evaluation

In this stage, the performance of each algorithm will be evaluated using a confusion matrix, which is a model for assessing the performance of algorithms in supervised learning. The matrix presents the columns as the classes predicted by the model (Predicted Class) and the rows as the actual classes (Actual Class) [34].

The confusion matrix is a statistical tool used to evaluate the performance of a classification model. It comprises four key elements: true positive (TP), false positive (FP), true negative (TN), and false negative (FN). TP represents the number of correctly classified positive instances, while FP denotes the number of positive predictions that were incorrect because they actually corresponded to negative instances. Similarly, TN signifies the number of accurately classified negative instances, whereas FN represents the number of negative instances that were incorrectly predicted as positive. Table 1 illustrates the 2x2 matrix representation of the confusion matrix model.

Table 1. ***Confusion matrix*** **2x2**

Actual Class	**Predicted Class**	
	Positive	**Negative**
Positive	TP	FP
Negative	FN	TN

Once the values for each class have been obtained, the accuracy, precision, recall, and F1-score metrics are calculated [35]. These metrics can be calculated using equations (8) to (11):

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (8)$$

$$precision = \frac{TP}{TP+FP} \quad (9)$$

$$recall = \frac{TP}{TP+FN} \quad (10)$$

$$f1 - score = 2 \times \frac{precision \times recall}{precision + recall} \quad (11)$$

4 Results and Analysis

This chapter will present the findings of the research conducted in accordance with the methodology outlined in the previous chapter, beginning with the data collection phase and concluding with the model evaluation.

4.1 Data Collecting

The data scraping process yielded 2,000 reviews spanning the period from October 18 to 28, 2024. The data set comprises two columns: `rating` and `review`. The reviews are in the form of text reviews from PUBG Mobile users. The text contains a variety of symbols, numbers, emojis, and abbreviations in a nonstandard language, necessitating further analysis. Figure 2 illustrates some of the reviews collected through scraping techniques.

ISSN:2302-8149
e-ISSN:2540-9719

rating	review
5	Saya i mbape
5	Terbaik
1	luck is sucks
1	Event lol berubah ae lama
1	Game anjinkkk, berapa kali kau suruh login ulang aja terus setann,
1	game rusak bug loading screen stuck di 65% kadang frame berat
5	Bagus banget pokoknya 😊 😊 😊 😊 😊 😊 😊
5	Sudah lama tifak main pubg karna sibuk skrg donlud ulang mau masuk ke akun lama sudah tidak bisa mohon admin bantuan nya
5	Saya sangat senang untk main game satu ini
1	Game kebanyakan cheater

Figure 2. Data scraping results

4.2 Data Labeling

The data collected for the PUBG Mobile review has been labeled according to the rating assigned by the user. The labeling results indicate that there are 849 positive reviews and 979 negative reviews. The removal of rating 3 reviews resulted in null values for some columns, reducing the total number of data points from 2,000 to 1,828. Figure 3 illustrates the outcomes of rating-based labeling, while Figure 4 presents a visualization of the results of sentiment labeling for PUBG Mobile app reviews.

rating	label	review
5	Positif	Saya i mbape
5	Positif	Terbaik
1	Negatif	luck is sucks
1	Negatif	Event lol berubah ae lama
1	Negatif	Game anjinkkk, berapa kali kau suruh login ulang aja terus setann,
1	Negatif	game rusak bug loading screen stuck di 65% kadang frame berat
5	Positif	Bagus banget pokoknya 😊 😊 😊 😊 😊 😊 😊
5	Positif	Sudah lama tifak main pubg karna sibuk skrg donlud ulang mau masuk ke akun lama sudah tidak bisa mohon admin bantuan nya
5	Positif	Saya sangat senang untk main game satu ini
1	Negatif	Game kebanyakan cheater

Figure 3. Labeling result based on rating

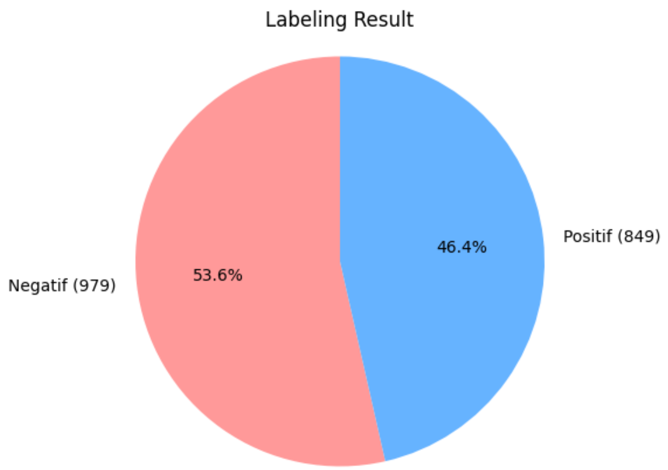

Figure 4. Visualization of labeling results

4.3 Data Preprocessing

This stage facilitates the generation of a more refined and organized corpus of review data through a series of preprocessing operations.

ISSN:2302-8149
e-ISSN:2540-9719

Table 2. Data preprocessing results

Before Preprocessing	
Review	Game Jelek gak Bisa Dimainkan game haram 1gb Doang Gak Bisa Dimainin
After Preprocessing	
Cleaning Data	Game Jelek gak Bisa Dimainkan game haram gb Doang Gak Bisa Dimainin
Case Folding	game jelek gak bisa dimainkan game haram gb doang gak bisa dimainin
Normalization	game jelek tidak bisa dimainkan game haram gb doang tidak bisa dimainin
Tokenization	['game', 'jelek', 'tidak', 'bisa', 'dimainkan', 'game', 'haram', 'gb', 'doang', 'tidak', 'bisa', 'dimainin']
Stopword Removal	['game', 'jelek', 'dimainkan', 'game', 'haram', 'gb', 'doang', 'dimainin']
Stemming	game jelek main game haram gb doang main

Table 2 illustrates the outcomes of the preprocessing stage. Following this stage, null values are removed, resulting in a total of 1,786 remaining review data points. This ensures the quality of the data to be processed in the subsequent stage.

4.4 Word Cloud Visualization

The objective of this study is to provide a more comprehensive understanding of the responses and perceptions of PUBG Mobile users. To this end, the presentation of the analysis results is divided into two distinct sections, one for positive reviews and one for reviews containing negative sentiments.

Figure 5. Word cloud positive reviews

Figure 5 presents a word cloud for the positive reviews, showcasing the key terms that reflect the aspects most highly rated by users. The most prevalent words, including "bagus", "mantap", "seru", "suka", and "keren", indicate a general satisfaction with the game. Additionally, there are words related to specific game features and elements, such as "player", "skin", "grafik", and "season", which suggest that users appreciate the quality of graphics and gameplay in PUBG Mobile.

 ISSN:2302-8149
e-ISSN:2540-9719

Figure 6. Word cloud negative reviews

Figure 6 presents the word cloud for negative reviews, which provides a clear representation of the primary topics that users have identified as problematic. The term "bug" indicates the frequency of technical issues encountered by players. Other technical concerns are reflected in words such as "lag", which indicates response delays, "frame" which pertains to frame rate instability, and "berat" which signifies performance issues on the device. Additionally, the words "parah", "jelek", and "buruk" suggest user dissatisfaction.

4.5 Data Splitting

The preprocessed data will be divided into two distinct sets: the training data (80%) and the testing data (20%). This division is intended to guarantee that the model is trained and evaluated in an objective manner. The result of this partitioning is 1,428 training data points and 358 test data points. The visualization of the data division results can be seen in Figure 7.

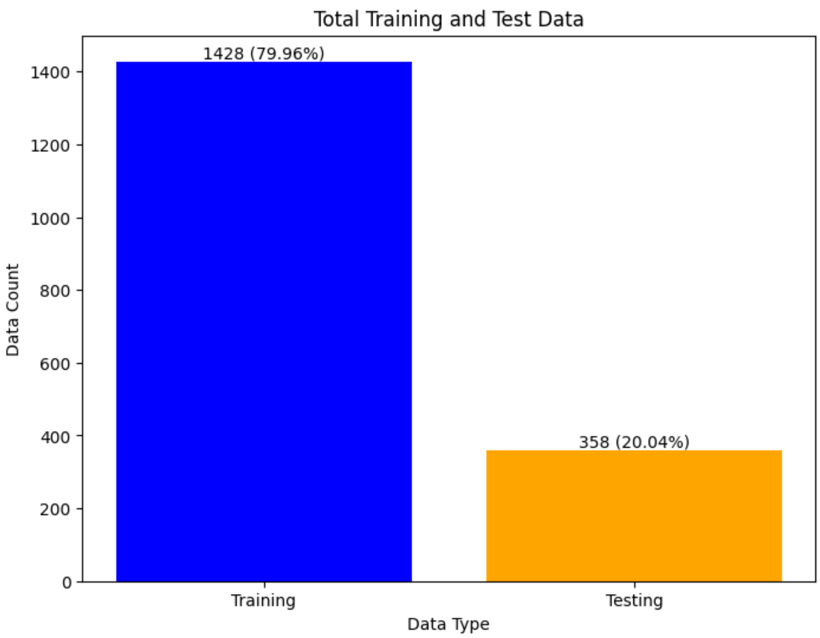

Figure 7. Data splitting visualization

4.6 Term Frequency-Inverse Document Frequency Weighting

The TF-IDF method is employed to assign weights to terms within a text, thereby enabling the effective identification of pivotal words. TF-IDF weighting identifies terms that are frequently utilized

ISSN:2302-8149
e-ISSN:2540-9719

in a review but have a low frequency of occurrence in the corpus as a whole, thus facilitating a more profound comprehension of the users' perspectives. Table 3 illustrates the TF-IDF value of each term present in the PUBG Mobile review dataset.

Table 3. TF-IDF weighting result

Feature	TF-IDF	Document
kemarin	0.775418	0
buka	0.357146	0
lancar	0.314136	0
kayak	0.264996	0
update	0.205806	0
…	…	…
merespon	0.260292	1427
server	0.214781	1427
game	0.196558	1427
masuk	0.183426	1427

4.7 Classification Model Implementation

The implementation of the Naive Bayes algorithm is done using the `scikit-learn` library with the `MultinomialNB` class. The model is trained using training data that has gone through the TF-IDF process, the default parameter is used to classify reviews into two categories, namely positive and negative, based on the probability of occurrence of words in the dataset. Meanwhile, the implementation of the SVM algorithm is done using the `LinearSVC class`, which implements support vector classification for the linear case. The selection of the linear kernel is based on the characteristics of text data, which can generally be separated linearly after TF-IDF transformation.

4.8 Model Evaluation

The performance of the two models will be evaluated using a confusion matrix. This evaluation aims to assess the efficacy of each algorithm in classifying the sentiment expressed in PUBG Mobile reviews as positive or negative.

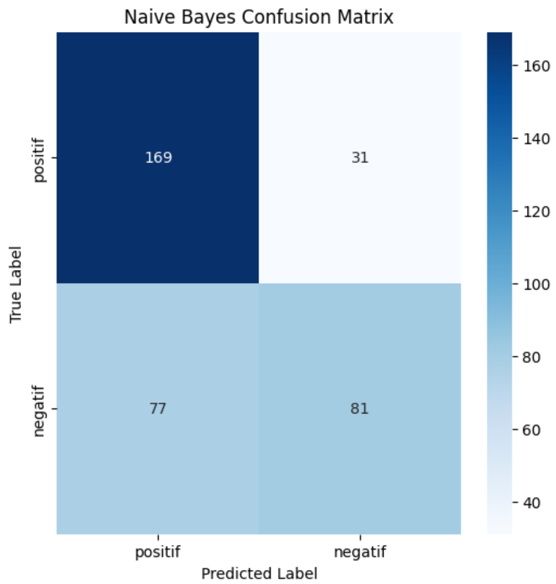

Figure 8. Naive bayes confusion matrix

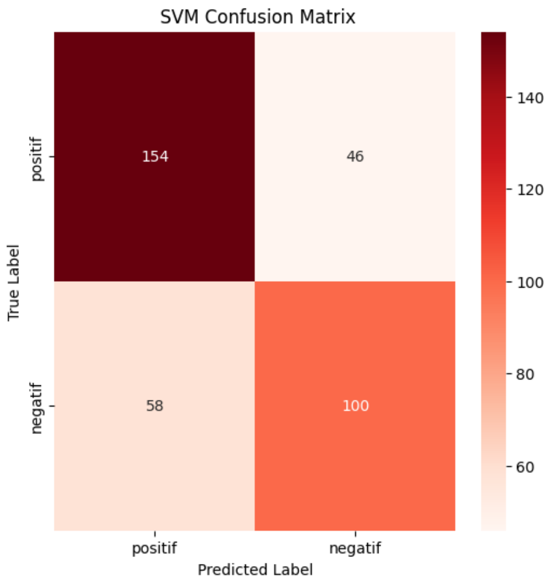

Figure 9. SVM confusion matrix

 ISSN:2302-8149
e-ISSN:2540-9719

Figures 8 and 9 illustrate the predictive outcomes of the two models in classifying the sentiment of PUBG Mobile reviews. Out of the 358 test data points, the Naive Bayes algorithm correctly identified 169 instances of positive sentiment and 81 instances of negative sentiment. In comparison, the Support Vector Machine (SVM) algorithm correctly identified 154 instances of positive sentiment and 100 instances of negative sentiment. This illustrates the superior performance of the Support Vector Machine (SVM) in identifying positive and negative sentiments in PUBG Mobile reviews, particularly in comparison to the Naive Bayes algorithm.

Table 4. Model performance results

Model	Accuracy	Precition	Recall	F1-Score
Naïve Bayes	69.83%	70.30%	69.83%	68.82%
SVM	70.95%	70.81%	70.95%	70.80%

To ascertain the efficacy of the Naive Bayes and SVM models in classifying sentiment, one may refer to Table 4. This table presents the values of metrics such as accuracy, precision, recall, and F1-score. Furthermore, Figure 10 provides a visual representation of the performance comparison of the two models.

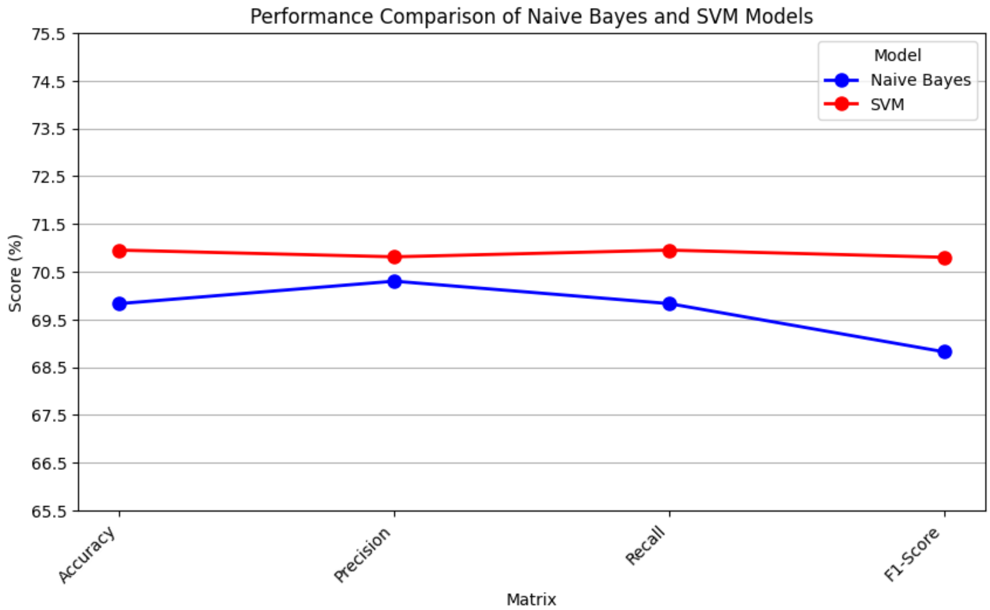

Figure 10. Model performance comparison chart

With regard to the accuracy metric, the Support Vector Machine (SVM) model achieved a value of 70.95%, while the Naive Bayes model exhibited a lower level of accuracy at 69.83%. With regard to precision, the Support Vector Machine (SVM) exhibited superior performance, achieving a value of 70.81% in comparison to 70.30% for Naive Bayes. With regard to recall, the Support Vector Machine (SVM) once again demonstrates superior reliability, with a value of 70.95%, in comparison to the 69.83% observed for Naive Bayes. A notable discrepancy was observed in the F1-Score metric, where the Support Vector Machine (SVM) attained a value of 70.80%, while the Naive Bayes model only reached 68.82%. However, the training process of the Naive Bayes model was more expeditious, with a duration of only 0.00 seconds, whereas the Support Vector Machine (SVM) training process required 0.02 seconds.

5 Conclusion

The analysis of the research data revealed that users of PUBG Mobile expressed high levels of satisfaction with the quality of the graphics and gameplay. However, some users also reported technical issues, including lag, unstable servers, bugs, and suboptimal performance. The performance evaluation of the sentiment classification model indicated that the Support Vector Machine (SVM) algorithm obtained the best results, with an accuracy of 70.95%, precision of 70.81%, recall of 70.95%, and F1-

ISSN:2302-8149
e-ISSN:2540-9719

Score of The accuracy, precision, recall, and F1-score of the SVM were 70.80%, 70.30%, 69.83%, and 68.82%, respectively. In comparison, the Naïve Bayes achieved an accuracy of 69.83%, precision of 70.30%, recall of 69.83%, and F1-score of 68.82%. Notwithstanding, Naïve Bayes exhibits a superior computational speed, requiring only 0.00 seconds for training, in comparison to SVM, which necessitates 0.02 seconds. The findings indicate that the developers of PUBG Mobile should prioritize improvements in technical aspects, particularly in regard to server stability, performance optimization, anti-cheat system, and regular maintenance, with the aim of enhancing the user experience. For future research, it is recommended to explore the use of other machine learning algorithms, such as deep learning or ensemble methods, as well as consider multilabel sentiment analysis to identify specific aspects commented on.

References

[1] R. J. Santi, D. Setiawa, and I. A. Pratiwi, "Perubahan Tingkah Laku Anak Sekolah Dasar Akibat Game Online," *Jurnal Penelitian dan Pengembangan Pendidikan*, vol. 5, no. 3, pp. 385–390, 2021, doi: 10.23887/jppp.v5i3.38576.

[2] S. Irawan and D. S. W., "Faktor-Faktor Yang Mempengaruhi Kecanduan Game Online Peserta Didik," *Jurnal Konseling Gusjigang*, vol. 7, no. 1, pp. 9–19, 2021, doi: 10.24176/jkg.v7i1.5646.

[3] B. Kamajaya, "Hubungan Kompetensi Sosial dengan Kecanduan Game Online pada Komunitas Players Unknown's Battlegrounds (PUBG) Mobile," *Psikoborneo: Jurnal Ilmiah Psikologi*, vol. 8, no. 1, pp. 33–39, 2020, doi: 10.30872/psikoborneo.v8i1.

[4] C. Cahyaningtyas, Y. Nataliani, and I. R. Widiasari, "Analisis Sentimen pada Rating Aplikasi Shopee Menggunakan Metode Decision Tree dengan SMOTE," *AITI: Jurnal Teknologi Informasi*, vol. 18, no. 2, pp. 173–184, 2021, doi: 10.24246/aiti.v18i2.173-184.

[5] M. Haikal, Martanto, and U. Hayati, "Analisis Sentimen terhadap Penggunaan Aplikasi Game Online PUBG Mobile Menggunakan Algoritma Naive Bayes," *JATI (Jurnal Mahasiswa Teknik Informatika)*, vol. 7, no. 6, 2023, doi: 10.36040/jati.v7i6.8174.

[6] Y. Firmansyah, R. Kurniawan, and Y. A. Wijaya, "Analisis Data Sentimen Pemain Game Role-Playing Game (RPG) Honkai Star Rail dengan Algoritma Naive Bayes," *Jurnal Informatika dan Rekayasa Perangkat Lunak*, vol. 6, no. 1, pp. 127–135, 2024, doi: 10.36499/jinrpl.v6i1.10243.

[7] A. Setiawan and R. R. Suryono, "Analisis Sentimen Ibu Kota Nusantara menggunakan Algoritma Support Vector Machine dan Naïve Bayes," *Edumatic: Jurnal Pendidikan Informatika*, vol. 8, no. 1, pp. 183–192, 2024, doi: 10.29408/edumatic.v8i1.25667.

[8] H. Junianto, P. Arsi, B. A. Kusuma, and D. I. S. Saputra, "Evaluasi Aplikasi Raileo Melalui Analisis Sentimen Ulasan Playstore Dengan Metode Naive Bayes," *SINTECH JOURNAL*, vol. 7, no. 1, pp. 27–40, 2024, doi: 10.31598/sintechjournal.v7i1.1505.

[9] A. W. V. Hutabarat, N. L. S. S. Adnyani, and K. Suryadi, "Analisis Sentimen Data Ulasan Pengguna MyPertamina di Twitter dengan Metode Machine Learning dan Deep Learning," *Jurnal Rekayasa Sistem Industri*, vol. 13, no. 1, pp. 145–154, 2024, doi: 10.26593/jrsi.v13i1.6958.145-154.

[10] A. H. Nurdy, A. Rahim, and Arbansyah, "Analisis Sentimen Ulasan Game Stumble Guys Pada Playstore Menggunakan Algoritma Naïve Bayes Sentiment Analysis of Stumble Guys Game Reviews on Playstore Using the Naïve Bayes Algorithm," *Teknika*, vol. 13, no. November, pp. 388–395, 2024, doi: 10.34148/teknika.v13i3.993.

[11] E. R. Kaburuan and N. R. Setiawan, "Sentimen Analisis Review Aplikasi Digital Korlantas Pada Google Play Store Menggunakan Metode SVM," *Jurnal Sisfokom (Sistem Informasi dan Komputer)*, vol. 12, no. 1, pp. 105–116, 2023, doi: 10.32736/sisfokom.v12i1.1614.

[12] Y. Yu, T. Dinh, F. Yu, and V.-N. Huynh, "Understanding Mobile Game Reviews Through Sentiment Analysis: A Case Study of PUBGm," *Japan Advanced Institute of Science and Technology (JAIST)*, pp. 102–115, 2023, doi: 10.1007/978-3-031-49333-1_8.

[13] F. I. Wibowo and A. Febriandirza, "Analisis Sentimen Ulasan Pengguna Game Pubg Di Google Play Store Menggunakan Algoritma Naïve Bayes," *Jurnal Sistem Komputer dan Informatika (JSON)*, vol. 5, no. 3, pp. 590–599, 2024, doi: 10.30865/json.v5i3.7264.

[14] G. P. Permana, D. A. Nugraha, and H. Santoso, "Perbandingan Performa SVM dan Naïve Bayes Pada Analisis Sentimen Aplikasi Game Online," *JOINTECS (Journal of Information Technology and Computer Science)*, vol. 8, no. 1, pp. 21–30, 2024.

[15] L. B. Ilmawan and M. A. Mude, "Perbandingan Metode Klasifikasi Support Vector Machine dan Naïve Bayes untuk Analisis Sentimen pada Ulasan Tekstual di Google Play Store," *ILKOM Jurnal Ilmiah*, vol. 12, no. 2, pp. 154–161, 2020, doi: 10.33096/ilkom.v12i2.597.154-161.

[16] E. S. Romaito, M. K. Anam, Rahmaddeni, and A. N. Ulfah, "Perbandingan Algoritma SVM Dan NBC Dalam Analisa Sentimen Pilkada Pada Twitter," *CSRID Journal*, vol. 13, no. 3, pp. 169–179, 2021, doi: 10.22303/csrid.13.3.2021.169-179.

[17] R. Syahputra, G. J. Yanris, and D. Irmayani, "SVM and Naïve Bayes Algorithm Comparison for User Sentiment Analysis on Twitter," *Sinkron : Jurnal dan Penelitian Teknik Informatika*, vol. 7, no. 2, pp. 671–678, 2022, doi: 10.33395/sinkron.v7i2.11430.

[18] A. A. Munandar, Farikhin, and C. E. Widodo, "Sentimen Analisis Aplikasi Belajar Online Menggunakan Klasifikasi SVM," *(JOINTECS) Journal of Information Technology and Computer Science*, vol. 8, no. 2, pp. 77–84, 2023.

[19] D. Nurmalasari, T. I. Hermanto, and I. M. Nugroho, "Perbandingan Algoritma SVM, KNN dan NBC Terhadap Analisis Sentimen Aplikasi Loan Service," *JURNAL MEDIA INFORMATIKA BUDIDARMA*, vol. 7, no. 3, pp. 1521–1530, 2023.

[20] A. Mustolih, P. Arsi, and P. Subarkah, "Sentiment Analysis Motorku X using Applications Naive Bayes Classifier Method," *Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)*, vol. 6, no. 2, pp. 231 – 242, 2023, doi: 10.24014/ijaidm.v6i2.24864.

[21] A. Fauzi and A. H. Yunial, "Analisis Sentimen US Airline Pada Media Sosial Twitter/X Menggunakan Perbandingan Algoritma Data Mining," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 10, no. 2, pp. 277–286, 2024, doi: 10.26418/jp.v10i2.76024.

[22] O. P. Zusrotun, A. C. Murti, and R. Fiati, "Sentimen Analisis Belajar Online di Twitter Menggunakan Naïve Bayes," *Jurnal Nasional Pendidikan Teknik Informatika : JANAPATI*, vol. 11, no. 3, pp. 310–320, 2022, doi: 10.23887/janapati.v11i3.49160.

[23] F. Nufairi, N. Pratiwi, and F. Herlando, "Analisis Sentimen pada Ulasan Aplikasi Threads di Google Play Store Menggunakan Algoritma Support Vector Machine," *JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 9, no. 1, pp. 339–348, 2024, doi: 10.29100/jipi.v9i1.4929.

[24] R. Q. Rohmansa, N. Pratiwi, and M. J. Palepa, "Analisis Sentimen Ulasan Pengguna Aplikasi Discord Menggunakan Metode K-Nearest Neighbor," *JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 9, no. 1, pp. 368–378, 2024, doi: 10.29100/jipi.v9i1.4943.

[25] A. Hendra and Fitriyani, "Analisis Sentimen Review Halodoc Menggunakan Nai¨ve Bayes Classifier," *JISKA (Jurnal Informatika Sunan Kalijaga)*, vol. 6, no. 2, pp. 78–89, 2021, doi: https://doi.org/10.14421/jiska.2021.6.2.78-89.

[26] S. Lestari and S. Saepudin, "Support Vector Machine : Analisis Sentimen Aplikasi Saham di Google Play Store," *JUSIFO (Jurnal Sistem Informasi)*, vol. 7, no. 2, pp. 81–90, 2021, doi: 10.19109/jusifo.v7i2.9825.

[27] J. J. A. Limbong, I. Sembiring, and K. D. Hartomo, "Analisis Klasifikasi Sentimen Ulasan pada E-Commerce Shopee Berbasis Word Cloud dengan Metode Naive Bayes dan K-Nearest Neighbor," *Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK)*, vol. 9, no. 2, pp. 347–356, 2022, doi: 10.25126/jtiik.202294960.

[28] B. R. Ansyahry and I. H. Al Amin, "Klasifikasi Opini Masyarakat terhadap Jasa Ekspedisi J&T Express pada Media Sosial Twitter dengan Naïve Bayes," *Jurnal Teknologi Sistem Informasi dan Aplikasi*, vol. 6, no. 3, pp. 402–407, 2023, doi: 10.32493/jtsi.v6i3.30878.

[29] A. Syafi'i1, M. Afdal, E. Saputra, and R. Novita, "Analisis Sentimen Ulasan Pengguna Aplikasi Penjualan Pulsa Menggunakan Algoritma Naïve Bayes Classifier," *Jurnal Teknologi Sistem Informasi dan Aplikasi*, vol. 7, no. 3, pp. 1300–1308, 2024, doi: 10.32493/jtsi.v7i3.41364.

[30] S. A. Azzahra and A. Wibowo, "Analisis Sentimen Multi-Aspek Berbasis Konversi Ikon Emosi dengan Algoritme Naïve Bayes Untuk Ulasan Wisata Kuliner pada Web Tripadvisor," *Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK)*, vol. 7, no. 4, pp. 737–744, 2020, doi: 10.25126/jtiik.202071907.

[31] S. Mulya, H. Sujaini, and Tursina, "Analisis Sentimen Tren Olahraga di Masa Pandemi COVID-19 pada Twitter dengan Metode Naïve Bayes Classifier (NBC)," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 8, no. 2, pp. 284–291, 2022, doi: 10.26418/jp.v8i2.52815.

[32] W. Silalahi and A. Hartanto, "Klasifikasi Sentimen Support Vector Machine Berbasis Optimasi Menyambut Pemilu 2024," *Jurnal Riset Sains dan Teknologi*, vol. 7, no. 2, pp. 245–255, 2023, doi: 10.30595/jrst.v7i2.18133.

[33] G. R. Ditami, E. F. Ripanti, and H. Sujaini, "Implementasi Support Vector Machine untuk Analisis Sentimen Terhadap Pengaruh Program Promosi Event Belanja pada Marketplace," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 8, no. 3, pp. 508–516, 2022, doi: 10.26418/jp.v8i3.56478.

[34] S. Khomsah and A. S. Aribowo, "Model Text-Preprocessing Komentar Youtube Dalam Bahasa Indonesia," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 4, no. 4, pp. 648 – 654, 2020, doi: 10.29207/resti.v4i4.2035.

[35] A. Rifa'i, H. Sujaini, and D. Prawira, "Sentiment Analysis Objek Wisata Kalimantan Barat Pada Google Maps Menggunakan Metode Naive Bayes," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 7, no. 3, pp. 400–407, 2021, doi: 10.26418/jp.v7i3.48132.