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Research Article [OPEN ACCESS]

Comparative Analysis of Naïve Bayes Classifier and Support Vector Machine for Multilingual Sentiment Analysis: Insights from Genshin Impact User Reviews

Rachell Aprinastya*, Muhammad Jazman, Syaifullah Syaifullah, Medyantiwi Rahmawita, Syafril Siregar, Eki Saputra

ABSTRACT

This study evaluates the performance of Support Vector Machine (SVM) and Naïve Bayes Classifier (NBC) algorithms in analyzing user sentiments regarding the popular online game Genshin Impact. The dataset comprises reviews sourced from the Google Play Store and App Store in both Indonesian and English, reflecting linguistic diversity. Preprocessing techniques such as tokenization, stemming, and Term Frequency-Inverse Document Frequency (TF-IDF) were employed to enhance data quality. Sentiments were classified as positive, neutral, or negative using TextBlob-assisted processes. Results demonstrate that NBC outperformed SVM across all metrics, with an average accuracy of 71% compared to 63%. Notably, sentiment analysis on English datasets consistently achieved higher accuracy than on Indonesian datasets, emphasizing the challenges posed by the linguistic complexity of Indonesian. This research underscores the critical role of language-specific adaptations in improving machine learning algorithms for multilingual sentiment analysis. The findings provide actionable insights for optimizing user engagement through enhanced game feedback mechanisms.

Keyword: Naïve bayes classifier, sentiment analysis, support vector machine

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Corresponding Author: Rachell Aprinastya, Department of Information System, Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia; 12050322191@students.uin-suska.ac.id
Authors: Muhammad Jazman, Department of Information System, Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia, jazman@uin-suska.ac.id; Syaifullah Syaifullah, Department of Information System, Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia, syaifullah@uin-suska.ac.id; Medyantiwi Rahmawita, Department of Information System, Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia, medyantiwi.rahmawita@uin-suska.ac.id; Syafril Siregar, Department of Information System, Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia, syafrilsrg@gmail.com; Eki Saputra, Department of Information System, Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia, eki.saputra@uin-suska.ac.id

1. INTRODUCTION

The gaming industry represents a significant advancement in modern technology and stands as one of the largest global industries today (Albaghajati & Ahmed, 2023). Gaming platforms include computers, smartphones, and gaming consoles, with options for both online and offline gameplay (Yakan, 2022). Among these, online gaming has become an integral daily activity for many, offering entertainment and challenges (Han et al., 2020). A 2020 report by Global Webindex indicated that 69% of internet users played games on smartphones, 41% on laptops or PCs, 25% on game consoles, 21% on tablets, and 81% on other devices. These statistics underscore the gaming industry's vast reach and influence in the technological era.

One notable example of a popular online game is Genshin Impact, launched by Cognosphere PTE. LTD. in 2020. The game is accessible via the Google Play Store for Android devices and the App Store for iOS devices. Genshin Impact has gained significant popularity in Indonesia, as evidenced by AppMagic data, which shows Indonesia ranked second worldwide for downloads, with 200,000 downloads in the past 30 days—surpassing countries like the United States, Brazil, and Japan. The substantial user base on both Android and iOS platforms highlights the importance of analyzing user experiences and feedback (Birjali et al., 2021).

Given the diverse user experiences and the active engagement of players in providing feedback, sentiment analysis offers a robust approach for developers to optimize the gaming experience. Sentiment analysis not only advances algorithmic development but also addresses the dynamic nature of digital communication (Kurnianingrum et al., 2023). By analyzing user sentiments, developers can gain deeper insights into preferences and grievances, enabling strategic decision-making for application development (Sharma & Goyal, 2023; Wankhade et al., 2022). Such insights allow developers to implement targeted improvements, enhancing user satisfaction and loyalty while effectively reducing churn rates (Juandri et al., 2024).

However, the efficacy of sentiment analysis depends significantly on the linguistic context. Algorithms optimized for English often fail to perform adequately when applied to Indonesian, due to the unique linguistic patterns and figurative expressions present in the language (Dronne, 2023; Fauziah et al., 2021; Kathunia et al., 2024). This research leverages machine learning techniques, specifically the Support Vector Machine (SVM) and Naïve Bayes Classifier (NBC), to perform sentiment analysis on reviews of Genshin Impact.

A recent comparative study by Safrudin et al. (2024) analyzed game reviews using SVM and NBC algorithms, with data sourced from game review platforms, social media, and user forms. Results indicated that SVM achieved an accuracy of 83%, outperforming NBC's accuracy of 75.5%. These findings underscore SVM's effectiveness in sentiment analysis for Genshin Impact reviews. Despite such studies, limited research has been conducted on game reviews in Indonesian, which often contain unique linguistic characteristics that influence algorithmic accuracy. This gap emphasizes the need for further research.

The present study aims to compare the performance of the Naïve Bayes Classifier and Support Vector Machine algorithms in analyzing user sentiment regarding Genshin Impact. By incorporating both English and Indonesian datasets, this research seeks to advance sentiment analysis methodologies, providing valuable insights into the implications of linguistic diversity in online game feedback.

2. MATERIALS AND METHODS

2.1 Materials

The comparative evaluation of algorithms for sentiment analysis has been a key focus of several studies. Golpour et al. (2020) assessed the performance of the Naïve Bayes Classifier, Support Vector Machine (SVM), and Logistic Regression algorithms in predicting the necessity of Coronary Angiography procedures. The study revealed that the Naïve Bayes Classifier outperformed the other algorithms, requiring only three models to achieve accurate predictions. In contrast, the Support Vector Machine ranked second with six models, while Logistic Regression demonstrated lower efficacy.

Similarly, Dey et al. (2020) explored the efficacy of the Naïve Bayes Classifier and Support Vector Machine algorithms in analyzing sentiment from Amazon product reviews. The data were categorized into four groups: true positive, true negative, false positive, and false negative. Their findings demonstrated that the Support Vector Machine outperformed the Naïve Bayes Classifier, achieving an accuracy of 84% compared to 82.88%.

Another study conducted by Ma et al. (2020) utilized the Support Vector Machine and Naïve Bayes Classifier algorithms to classify spam emails based on subject and content. The results highlighted the importance of training data volume, as both algorithms exhibited improved accuracy with larger datasets. Among the two, the Support Vector Machine demonstrated superior performance, achieving an accuracy of 95.5%.

Putri et al. (2020) further compared the Naïve Bayes Classifier and Support Vector Machine algorithms for sentiment analysis of E-Wallet reviews, employing the PSO (Particle Swarm Optimization) feature selection technique to enhance performance. The study revealed that the PSO-enhanced Naïve Bayes

Classifier achieved an accuracy of 93.10% with an AUC value of 0.750, categorized as "Satisfactory Classification." In comparison, the PSO-enhanced Support Vector Machine achieved an accuracy of 91.30% with an AUC value of 0.970, classified as "Very Good Classification."

These studies collectively underscore the variability in performance across different sentiment analysis tasks and datasets. While the Naïve Bayes Classifier demonstrated notable accuracy in certain contexts, the Support Vector Machine consistently emerged as a strong contender, particularly when paired with advanced optimization techniques.

2.2 Methods

This section describes the methodology employed in the study, which included data collection, preprocessing, sentiment labeling, and the application of TF-IDF for feature extraction. The research workflow is illustrated in Figure 1.

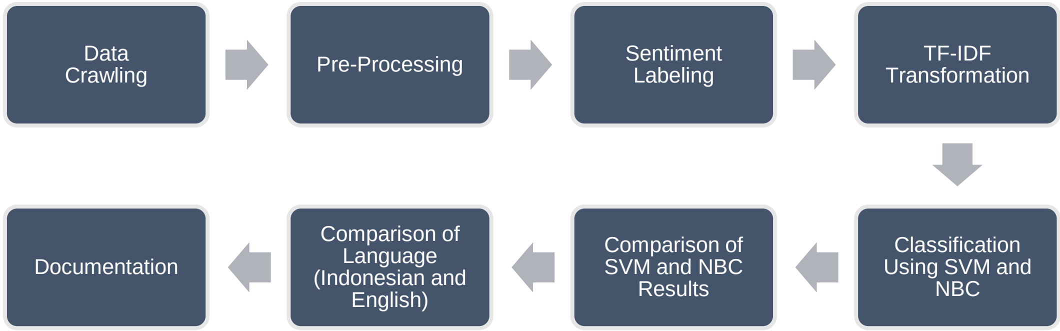


Figure 1. Research methodology workflow

Data collection was conducted using web scraping techniques facilitated by Google Colab tools. The dataset consisted of user reviews of the game Genshin Impact, which were extracted from the App Store and Google Play Store. To ensure linguistic diversity, the data included two types of reviews: one in Indonesian and the other in English.

To prepare the data for analysis, a preprocessing stage was implemented to clean and standardize the dataset, making it machine-readable and suitable for sentiment analysis. The preprocessing process included several critical steps. Data Cleaning was first performed to identify and correct errors in the dataset, improving its integrity. Case Folding followed, where all characters were converted to lowercase to ensure consistency. Stopword Removal was then conducted, eliminating irrelevant or less meaningful words based on a predefined stopword list. Afterward, Tokenizing segmented the text into smaller units, filtering out unimportant words that were not directly related to the application reviews. Finally, stemming reduced words to their root forms by removing affixes, ensuring uniformity and minimizing redundancy in the dataset (Nandwani & Verma, 2021).

Following preprocessing, the dataset was subjected to sentiment labeling, where each review was categorized as positive, negative, or neutral (Azzahra et al., 2020). This step is critical, as the quality of sentiment labeling directly influences the performance of sentiment analysis algorithms (Mitra & Mohanty, 2021). An imbalanced distribution of sentiment labels can lead to skewed algorithmic outcomes (Bekker & Davis, 2020). For instance, datasets dominated by positive labels can cause algorithms to overclassify data as positive, reducing their accuracy in identifying negative sentiments (Cole et al., 2021). Similarly, datasets heavily populated with neutral labels can impair an algorithm's ability to distinguish between positive and negative sentiments, resulting in classification errors (Chakraborty et al., 2020). Sentiment labeling in this study was conducted with the assistance of Python's TextBlob library for automatic processing.

To extract meaningful features from the text, the Term Frequency-Inverse Document Frequency (TF-IDF) method was applied. This statistical measure evaluates the importance of words within a document in relation to the entire dataset. Words that appear frequently in a specific document but infrequently across the corpus are assigned higher significance. This approach mitigates the issue of common words overshadowing more relevant terms, thereby enhancing the efficacy of classification algorithms (Dang et al., 2020).

To ensure robust performance and mitigate overfitting, the dataset was split into training and testing subsets using the Holdout Method. The training subset was used to train the model, while the testing subset served for evaluation purposes. This splitting technique enabled the model to generalize effectively to new, unseen data, ensuring reliable performance assessments and accurate predictions (Dhar et al., 2021).

3. RESULTS AND DISCUSSION

3.1 Data Collection and Crawling

Data collection was conducted using a scraping technique to extract user reviews of the game Genshin Impact from both the Google Play Store and the App Store. The process was implemented in Python through Google Colab, resulting in a total of 1,000 entries. Language-specific parameters were applied during the crawling process: lang='id' was used to collect reviews in Indonesian, and lang='eng' was utilized to gather reviews in English. The outcomes of this data collection process are illustrated in Figure 2, which presents an overview of the consumer reviews gathered for further analysis.

	userName	score	at	content
0	noxnox	1	2024-10-07 13:37:39	game kikir
1	Muhammad Ja'far Al-Harits Wijaya	1	2024-10-05 17:56:57	Makin susah yah,harus punya banyak karakter me...
2	KING NICO	1	2024-10-04 01:37:29	game kikir story bapuk karakter jelek ndk kaya...
3	Zip Knot	1	2024-10-02 03:59:52	hype saya pada ini game sudah hilang
4	frendy tan	1	2024-09-30 16:32:22	login dipersulit!!!! selalu terlalu banyak per...

Figure 2. Crawling data output

3.2 Data Pre-Processing

Following the data crawling stage, the collected dataset underwent a pre-processing phase to ensure quality and compatibility for subsequent sentiment analysis. This phase involved several critical steps, which are summarized in Table 1, detailing the transformation of raw text into a structured format suitable for analysis. The first step, Data Cleaning, involved identifying and correcting errors in the dataset. For example, extraneous characters and formatting issues were removed to enhance data quality. Next, Casefolding was applied, where all text was converted to lowercase to maintain uniformity. Subsequently, Stopword Removal eliminated irrelevant words with minimal meaning in the context of sentiment analysis. For instance, common function words like "and" and "the" were excluded.

The Tokenizing step divided the text into smaller units, or tokens, allowing the isolation of meaningful words relevant to sentiment analysis. Finally, Stemming was applied to reduce words to their base forms by removing affixes, ensuring consistency, and reducing redundancy.

Table 1. Text pre-processing workflow: before and after

Text Pre-Processing Workflow	Before	After
Data Cleaning	grafik bagus, story jg dewa bgt cuman pas ngerjain quest kadang frustasi bgt sama puzzle nya (TAPII SERU BGT PAS NGERJAIN).	grafik bagus story jg dewa bgt cuman pas ngerjain quest kadang frustasi bgt sama puzzle nya TAPII SERU BGT PAS NGERJAIN
	Iâ€™ve been playing Genshin Impact for about a year now and the day I downloaded this game I fell in love with it	Ive been playing genshin impact for about a year now and the day I downloaded this game I fell in love with it

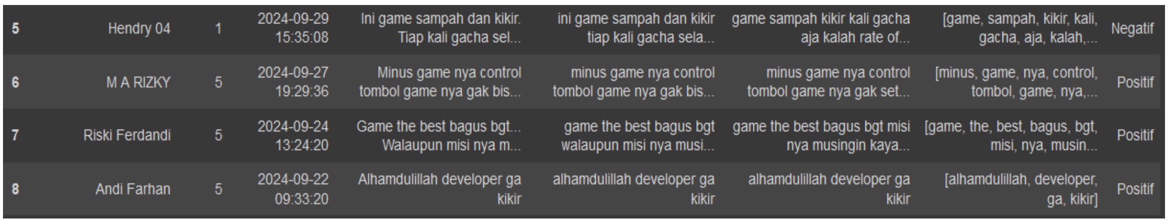
Table 1. Text pre-processing workflow: before and after (continued)

Text Pre-Processing Workflow	Before	After
Casefolding	grafik bagus story jg dewa bgt cuman pas ngerjain quest kadang frustasi bgt sama puzzle nya TAPII SERU BGT PAS NGERJAIN	grafik bagus story jg dewa bgt cuman pas ngerjain quest kadang frustasi bgt sama puzzle nya tapii seru bgt pas ngerjain
	Ive been playing genshin impact for about a year now and the day I downloaded this game I fell in love with it	ive been playing genshin impact for about a year now and the day i downloaded this game i fell in love with it
Stopword Removal	grafik bagus story jg dewa bgt cuman pas ngerjain quest kadang frustasi bgt sama puzzle nya tapii seru bgt pas ngerjain	grafik bagus story jg dewa bgt cuman pas ngerjain quest kadang frustasi bgt puzzle nya tapii seru bgt pas ngerjain
	ive been playing genshin impact for about a year now and the day i downloaded this game i fell in love with it	ive playing genshin impact year day downloaded game fell love
Tokenizing	grafik bagus story jg dewa bgt cuman pas ngerjain quest kadang frustasi bgt puzzle nya tapii seru bgt pas ngerjain	['grafik', 'bagus', 'story', 'jg', 'dewa', 'bgt', 'cuman', 'pas', 'ngerjain', 'quest', 'kadang', 'frustasi', 'bgt', 'puzzle', 'nya', 'tapii', 'seru', 'bgt', 'pas', 'ngerjain']
	ive playing genshin impact year day downloaded game fell love	['ive', 'playing', 'genshin', 'impact', 'year', 'day', 'downloaded', 'game', 'fell', 'love'
Stemming	grafik bagus story jg dewa bgt cuman pas ngerjain quest kadang frustasi bgt puzzle nya tapii seru bgt pas ngerjain	grafik bagus story dewa cuma kerja quest frustasi puzzle seru
	ive playing genshin impact year day downloaded game fell love	I play genshin impact year day download game fell love

3.3 Sentiment Labeling

The pre-processed data was subjected to sentiment labeling, where each review was categorized as positive, negative, or neutral. This step utilized Python programming tools to automate the labeling process. The sentiment distribution for Indonesian data is depicted in Figure 3, while results for English data are shown in Figure 4.

For the dataset in Indonesian, the Google Play Store reviews yielded 249 positive, 26 neutral, and 75 negative sentiments, while the App Store reviews showed 185 positive, 15 neutral, and 160 negative sentiments. Conversely, the English dataset from the Google Play Store contained 286 positive, 16 neutral, and 48 negative sentiments, whereas the App Store data included 268 positive, 44 neutral, and 48 negative sentiments. The results highlight variations in sentiment distribution across platforms and languages, providing a foundation for further analysis of user perceptions and experiences with Genshin Impact.



5	Hendry 04	1	2024-09-29 15:35:08	Ini game sampah dan kikir. Tiap kali gacha sel...	ini game sampah dan kikir tiap kali gacha sela...	game sampah kikir kali gacha aja kalah rate of...	[game, sampah, kikir, kali, gacha, aja, kalah,...	Negatif
6	M A RIZKY	5	2024-09-27 19:29:36	Minus game nya control tombol game nya gak bis...	minus game nya control tombol game nya gak bis...	minus game nya control tombol game nya gak set...	[minus, game, nya, control, tombol, game, nya,...	Positif
7	Riski Ferdandi	5	2024-09-24 13:24:20	Game the best bagus bgt... Walaupun misi nya m...	game the best bagus bgt walaupun misi nya musi...	game the best bagus bgt misi nya musingin kaya...	[game, the, best, bagus, bgt, misi, nya, musin...	Positif
8	Andi Farhan	5	2024-09-22 09:33:20	Alhamdulillah developer ga kikir	alhamdulillah developer ga kikir	alhamdulillah developer ga kikir	[alhamdulillah, developer, ga, kikir]	Positif

Figure 3. Sentiment distribution in indonesian reviews

2	Anida Hardolli	3	2024-10-02 19:43:17	I love the games art style is very fun. The st...	i love the games art style is very fun the sto...	love games art style fun story characters also...	[love, games, art, style, fun, story, characte...	Netral
3	Yashdh Oyfh	5	2024-09-30 17:39:21	I have a different account on my ps5 but I for...	i have a different account on my ps but i forg...	different account ps forgot password	[different, account, ps, forgot, password]	Positif
4	Kaleb McWilliams	1	2024-09-30 00:05:02	No McDonald's collaboration anything like what...	no mcdonalds collaboration anything like what ...	mcdonalds collaboration anything like hell	[mcdonalds, collaboration, anything, like, hell]	Negatif
5	hendry jilen	1	2024-09-28 08:49:59	Requesting to get more sanctifying elixir but ...	requesting to get more sanctifying elixir but ...	requesting get sanctifying elixir customer ser...	[requesting, get, sanctifying, elixir, custome...	Negatif

Figure 4. Sentiment distribution in english reviews

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

The TF-IDF technique was applied to evaluate the significance of each word within the dataset. TF-IDF assigns higher weights to words that frequently appear in a specific document but are rare across the corpus. This process helps identify relevant terms while minimizing the impact of commonly used words.

The results of the TF-IDF analysis for the Indonesian dataset are shown in Table 2, and Table 3 presents the outcomes for the English dataset. These tables provide a sample of TF-IDF values, demonstrating the weighting of significant terms within the text data.

Table 2. Sample TF-IDF weights for indonesian dataset

No.	1	2	3	4	5	...	3465
	perbaiki	berat	rusak	mabar	rusuh	...	tim
1	0	0	0.367	0.177	0.367	...	0.219
2	0.141	0.522	0	0	0	...	0
...	0	0	0	0	0	...	0
1000	0	0.333	0	0.247	0	...	0.387

Table 3. Sample TF-IDF weights for english dataset

No.	1	2	3	4	5	...	13987
	close	exploring	farme	model	standout	...	title
1	0.213	0.863	0.546	0.818	0	...	0.895
2	0.647	0	0.353	0.356	0.827	...	0.543
...	0	0	0	0	0	...	0
1000	0	0.568	0	0	0	...	0

3.5 Support Vector Machine (SVM) Performance

The SVM algorithm was utilized to classify sentiments within the dataset. The data was divided into 80% for training and 20% for testing. This division ensured that the algorithm was trained on a substantial portion of the data while maintaining a separate subset for performance evaluation.

The results of the SVM algorithm are summarized in Table 4, which includes key performance metrics such as accuracy, precision, recall, and F1 score. For the App Store, the SVM algorithm achieved an accuracy of 50% for Indonesian and 75% for English. On the Google Play Store, the accuracy reached 60% for Indonesian and 67% for English.

Table 4. Performance metrics of the svm algorithm

Application	Indonesia				English			
	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
App Store	50%	47%	50%	48%	75%	61%	75%	67%
Google Play Store	60%	40%	60%	48%	67%	46%	67%	55%

3.6 Naïve Bayes Classifier (NBC) Performance

The NBC algorithm was also employed to classify sentiments within the dataset. Similar to the SVM approach, the data was split into 80% for training and 20% for testing. This division ensured consistency in the experimental setup, allowing for a direct comparison of the two algorithms.

The performance metrics of the Naïve Bayes Classifier are presented in Table 5, which includes accuracy, precision, recall, and F1 score for both Indonesian and English datasets. For the App Store, the NBC algorithm achieved an accuracy of 75% for Indonesian and 76% for English. On the Google Play Store, it attained an accuracy of 64% for Indonesian and 70% for English.

Table 5. Performance metrics of the nbc algorithm

Application	Indonesia				English			
	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
App Store	75%	73%	75%	73%	76%	65%	76%	69%
Google Play Store	64%	66%	88%	75%	70%	69%	98%	81%

3.7 Algorithm Comparison

This stage evaluates the relative performance of the SVM and NBC algorithms to determine which offers superior accuracy in sentiment analysis. The comparison results are illustrated in Figure 5, highlighting key performance metrics such as accuracy, precision, recall, and F1 score.

Overall, the NBC algorithm demonstrated superior performance across all evaluated metrics in this study, making it a more effective choice for sentiment classification. Specifically, NBC achieved an average accuracy of 71%, precision of 68%, recall of 84%, and F1 score of 74%, surpassing the SVM algorithm, which recorded an average accuracy of 63%, precision of 48%, recall of 63%, and F1 score of 54%. These results underscore the effectiveness of NBC over SVM in this context.

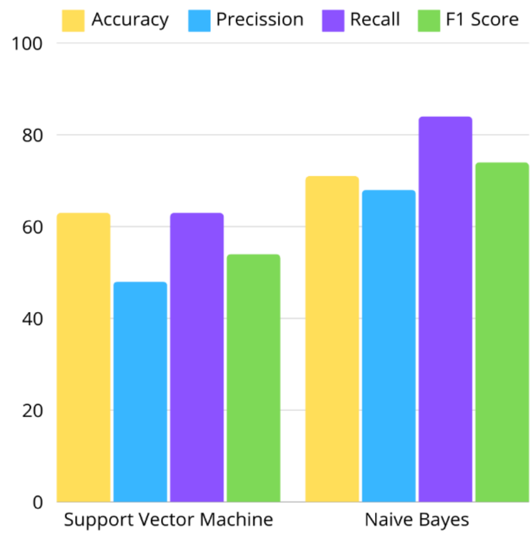


Figure 5. Performance comparison of svm and nbc algorithms

3.8 Language Performance Comparison

This stage focuses on evaluating the suitability of Indonesian and English datasets for sentiment analysis. The comparison was conducted using the average accuracy results obtained from the SVM and NBC algorithms. The data sources were distinguished based on language, and the findings are visualized in Figure 6.

For the Indonesian dataset, the SVM algorithm achieved an average accuracy of 55%, whereas the NBC algorithm significantly outperformed it with an average accuracy of 69%. Similarly, for the English dataset, SVM achieved an average accuracy of 71%, while NBC exhibited a slightly higher accuracy of 73%.

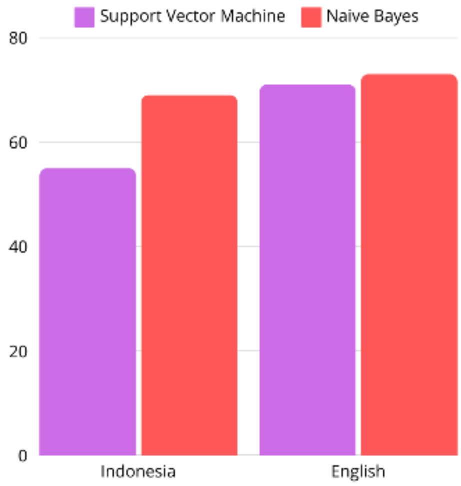


Figure 6. Comparison of sentiment analysis accuracy for indonesian and english datasets

3.9 Discussion

This study builds upon prior research by conducting a similar investigation using distinct datasets and diverse case studies. It expands upon previous work by incorporating a comparative analysis of sentiment analysis performance in both Indonesian and English. Specifically, this study evaluates the accuracy of two algorithms, SVM and NBC, in analyzing user sentiment from reviews of the game Genshin Impact. Additionally, it examines the comparative accuracy of sentiment analysis performed in Indonesian and English datasets.

The primary objective of this research was to identify which algorithm offers superior accuracy in capturing user sentiments from reviews obtained via the App Store and Google Play Store. By employing SVM and NBC algorithms, the study provides insights into their respective performance in multilingual contexts. Given the limited comparative research on the role of language in sentiment analysis, this study addresses this gap by integrating an evaluation of both Indonesian and English datasets to determine which language yields higher sentiment analysis accuracy.

Previous studies have highlighted challenges associated with applying machine learning techniques to Indonesian datasets. The linguistic characteristics of Indonesian, including its rich morphology and unique patterns, can complicate the machine learning process. Moreover, algorithms initially designed for English often struggle to maintain their accuracy when applied to datasets in other languages, including Indonesian. As a result, sentiment analysis using Indonesian data may not achieve the same level of accuracy as that performed on English datasets.

4. CONCLUSION

This study provides significant insights into sentiment analysis of user reviews for the game Genshin Impact using the NBC and SVM algorithms. The findings indicate that NBC consistently outperforms SVM in terms of accuracy, precision, recall, and F1 score across datasets in both Indonesian and English. With an average accuracy of 71% compared to 63% for SVM, NBC demonstrates its superior efficacy in sentiment classification, particularly in multilingual scenarios characterized by linguistic diversity such as those presented in this dataset.

Furthermore, the study highlights that sentiment analysis on English datasets achieves higher accuracy than on Indonesian datasets for both NBC and SVM. This finding underscores the challenges of sentiment analysis in Indonesian due to its complex morphology and unique linguistic expressions. Consequently, the study emphasizes the need for developing algorithms that are more adaptive to specific linguistic contexts, especially for languages with unique characteristics like Indonesian.

By offering a comprehensive comparative analysis of NBC and SVM in the domain of sentiment analysis for game reviews, this research contributes to the existing literature. The findings provide a solid foundation for future studies focused on developing more advanced and language-specific algorithms, thereby enhancing user experiences through optimized reviews and feedback mechanisms.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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