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Sentiment Analysis on ChatGPT App Reviews on Google Play Store Using Random Forest Algorithm, Support Vector Machine and Naïve Bayes

Gilbert Jeffson Sagala[1*], Yusran Timur Samuel[2]
Universitas Advent Indonesia Bandung, Indonesia
Email: gilbertjeffsonsagala@gmail.com[1*], y.tarihoran@unai.edu[2]

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ChatGPT; Random Forest; Support Vector Machine; Naïve Bayes; Google Play Store.

Abstract
This study aims to conduct a Sentiment Analysis on ChatGPT App reviews on the Google Play Store using three classification methods: Random Forest Algorithm, Support Vector Machine (SVM), and Naïve Bayes. The main purpose of this study is to detail and understand user sentiment towards the application. From a total of 2652 review data regarding ChatGPT performance from July 28, 2023, to January 28, 2024, the results were 2326 (87.71%) positive reviews and 326 (12.29%) negative reviews, which means that the public is more dominant in responding positively to the use of ChatGPT based on Google Play Store ratings. In this study, researchers used the f1-score to see which method works best because the data has an imbalance of data, so the f1-score is the best way to provide information about how well the model handles minority classes. Through the classification of three different algorithms with testing data taken from 796 (30%) from a total of 2652 rating reviews, it was found that Random Forest got an f1-score of 90% with positive correct data as much as 87.43% and negative accurate data as much as 0.75%, Support Vector Machine got an f1-score value of 90% with positive valid data as much as 86.80% and negative correct data as much as 0.13%, and Naïve Bayes received an f1-score of 87% with positive, accurate data of 88.06% and negative valid data of 0.12%. Therefore, it can be concluded from this study that users who experienced the development of the ChatGPT application felt a more striking positive impact, and the Support Vector Machine and Random Forest methods became the most effective methods in this study, proven by the highest f1-score value.

1. Introduction

The rapid development of computer-based information technology significantly impacts changes in various aspects of human life. Artificial Intelligence is the latest technology product resulting from rapid technological advances. Artificial Intelligence allows computers to carry out many tasks that humans do, making it a widely utilised technology product in application development today. This makes it easier for humans to meet their various needs (Rifaldi, Ramadhan, & Jaelani, 2023).

In November 2022, an AI research lab called OpenAI launched a chatbot application called ChatGPT. This chatbot is a natural language processing technology that can respond to human questions through text (prompts) typed in the application. What attracts a lot of attention is that the answers given by ChatGPT look well structured, the relationships between words or sentences are coherent, the accuracy is quite good, and they can remember previous conversations. As of November 2023, ChatGPT has 100 million weekly active users (Setiawan & Luthfiyani, 2023).

Reviews express a person's assessment of a product or service. Sentiment analysis helps us understand what customers think through their reviews about the product or service. These reviews can be a valuable source of information for consumers. For example, before buying a product, most people look for reviews about the product to help them make decisions (Hasibuan & Heriyanto, 2022). As a digital platform, Google Play Store allows users to share their experiences through app reviews.

In a study on PSBB sentiment analysis by comparing random forest classification methods and support vector machines conducted by Adrian et al. (Adrian, Putra, Rafialdy, & Rakhmawati, 2021), the results showed that the Random Forest algorithm had an accuracy rate of 58%, with precision, recall, and f1-score values of 35%, 58%, and 44% respectively. Meanwhile, the Support Vector Machine algorithm achieved an accuracy rate of 56%, with precision, recall, and f1-score values of 38%, 56%, and 44%, respectively. The performance of these two algorithms is considered low because the dataset used is very limited, consisting of only 466 tweet data (Ratnawati & Sulistyaningrum, 2020).

Then, research on sentiment analysis about the Ruangguru application using naïve bayes, random forest and support vector machine classification methods conducted by Evita Fitri et al. (Fitri, 2020) found that the Random Forest model had the highest accuracy of 97.16%, with AUC reaching 0.996. Meanwhile, the Support Vector Machine algorithm showed an accuracy of 96.01%, with an AUC of 0.543. On the other hand, the Naïve Bayes algorithm has the lowest accuracy, with a value of 94.16% and an AUC of 0.999 (Muslimin & Lusiana, 2023). Thus, based on the test results, it can be concluded that Random Forest performs better than the other two algorithms (Fernández-Gavilanes, Álvarez-López, Juncal-Martínez, Costa-Montenegro, & González-Castaño, 2016).

Based on the background description described in this study, the author chose the title "Sentiment Analysis on ChatGPT Application Reviews on the Google Play Store Using the Random Forest Algorithm Method, Support Vector Machine and Naïve Bayes". This study aims to see the accuracy of each classification method of the three methods and compare the three (Prayoginingsih & Kusumawardani, 2018).

2. Materials and Methods

This study is an experiment in sentiment analysis of ChatGPT reviews by applying Random Forest, Support Vector Machine, and Naïve Bayes classification models. The stages start from dataset retrieval, data labelling, text preprocessing, term weighting, algorithm implementation, classification results, and evaluation (Fitri, 2020).

Figure 1
Stages of Sentiment Analysis of ChatGPT reviews

Sentiment Analysis

Sentiment analysis is one of the techniques used to recognise an opinion or feeling conveyed through a text or document, as well as how that opinion is classified as positive or negative. Sentiment analysis seeks to evaluate various aspects in standard language to help an institution or company understand positive and negative opinions regarding the products they provide (Tuhuteru & Iriani, 2018).

The sentiment itself can be interpreted as an emerging concept in which everyone's different emotions are determined by the content of the text so that it can be processed to extract the opinions and sentiments of many people. In sentiment analysis, three views can guide agencies or companies to obtain information about the products' quality: positive, negative, and neutral (Klyueva, 2019).

Sentiment analysis is a new section of research in Natural Language Processing (NLP) that aims to find subjectivity in texts or documents to classify opinions or sentiments. Three techniques are generally applied in the sentiment classification method: Machine Learning, lexicon-based, and Hybrid Approach. Today, sentiment analysis often uses Machine Learning techniques because of the method's ability to predict sentiment polarity based on prepared data.

Dataset Collection

In performing sentiment analysis, data were collected from a review of the ChatGPT app on the Google Play Store. Data retrieval uses scraping techniques with Python libraries using Google Play Scraper. The data for this sentiment analysis is 2652 text reviews with the latest or most recent sorting reviews for the last 6 months, from July 28, 2023, to January 28, 2024.

Term Weighting

In this method, each word in the review will be given a weight or rating based on its significance in context. In other words, this method converts text into numbers that represent values. The technique used is TF-IDF (Term Frequency-Inverse Document Frequency), which combines the frequency of the term (F) and the presence of a term in the view that is irreva to the topi (IDF) [1]. The loin orla does the value of T each word. $\frac{Nmberf\ words\ tin\ document\ d}{total\ word\ count\ in\ docu\ d}$

(1)a $\frac{\text{Number of documents in the corpus}}{\text{number of documents in corpus d containing the word t}}$) (2)

After the TF and IDF values are obtained with the previous formula, TF-IDF can be obtained with the formula below.

$$\text{TF-IDF}(t, d, D) = \text{TF}(t, d) \times \text{IDF}(t, D) \quad (3)$$

3. Results and Discussions

In the initial phase, the study began with a dataset of 2652 review data collected from July 28, 2023, to January 28, 2024.

	reviewId	userName	userImage	content	score	thumbsUpCount	reviewCreatedVersion	at	replyContent	repliedAt	appVersion
0	8fa156a9-73a8-4b02-9b69-c0861a5c6c29	Nurul Khazanah putri	https://play-lh.googleusercontent.com/a/ACgBoc...	Bagus banget	5	0	1.2024.018	2024-01-28 09:36:53	None	NaT	1.2024.018
1	1fc9762f-6791-4b79-ab47-14f2018f67b07	Joy	https://play-lh.googleusercontent.com/a-/ALV-U...	Masi banyak kekeliruan dalam menjawab pertanya...	3	0	1.2024.018	2024-01-28 07:43:14	None	NaT	1.2024.018
2	3e2b34bd-261d-4e89-947b-bc6322ac25e4	Dani Saputra	https://play-lh.googleusercontent.com/a/ACgBoc...	keren ck	5	0	1.2024.018	2024-01-28 03:21:43	None	NaT	1.2024.018
3	770fe17a-2a26-46a2-9c83-40b2832bcb5f	Gamer Indo	https://play-lh.googleusercontent.com/a-/ALV-U...	this app soo cool, the ai can help my everyday	5	0	1.2024.018	2024-01-27 14:32:13	None	NaT	1.2024.018
4	fcaa0962-6bab-4883-8a0c-135342953601	Hinggil budhi Utomo	https://play-lh.googleusercontent.com/a-/ALV-U...	sangat bagus untuk menjawab tentang apapun	5	0	1.2024.010	2024-01-27 13:36:10	None	NaT	1.2024.010
...	...	...	...	...	...	...	...	...	...	...	...
2647	b224b73b-009b-46d8-8e4e-a21cecd96f8e	Rambutan Asem	https://play-lh.googleusercontent.com/a-/ALV-U...	Menurut saya aplikasi ini sudah oke untuk pemb...	5	0	1.0.0023	2023-07-28 13:34:15	None	NaT	1.0.0023
2648	b72e43e7-8795-4d13-b7d6-564899d07556	Arfa Bahy	https://play-lh.googleusercontent.com/a/ACgBoc...	Bagus sekali	5	0	None	2023-07-28 13:17:54	None	NaT	None
2649	ba7cbc99-a6f8-4545-a204-a354622ce3cb	Muhammad Rafly	https://play-lh.googleusercontent.com/a-/ALV-U...	Nice app	5	0	1.0.0023	2023-07-28 13:05:31	None	NaT	1.0.0023

Figure 2 Dataset Collection

After successfully collecting the dataset, the next step is to clean the data, such as removing emojis, numbers, and punctuation marks and changing uppercase letters to lowercase.

	content	score	cleaned_text	label	content_len	punct
2651	Menjadi yang pertama itu sangatlah baik	5	menjadi yang pertama itu sangatlah baik	1	34	0.0
2650	Next geoglee in blockchain ..... Barvo cryto ...	5	next geoglee in blockchain barvo cryto ...	1	46	10.9
2649	Nice app	5	nice app	1	7	0.0
2648	Bagus sekali	5	bagus sekali	1	17	0.0
2647	Menurut saya aplikasi ini sudah oke untuk pemb...	5	menurut saya aplikasi ini sudah oke untuk pemb...	1	60	0.0

Gambar 3 Data Cleansing and Case Folding

Furthermore, tokenising or separating text-type data into per word is carried out.

	content	score	cleaned_text	label	content_len	punct	tokens
2651	Menjadi yang pertama itu sangatlah baik	5	menjadi yang pertama itu sangatlah baik	1	34	0.0	[menjadi, yang, pertama, itu, sangatlah, baik]
2650	Next geoglee in blockchain ..... Barvo cryto ...	5	next geoglee in blockchain barvo cryto ...	1	46	10.9	[next, geoglee, in, blockchain, barvo, cryto]
2649	Nice app	5	nice app	1	7	0.0	[nice, app]
2648	Bagus sekali	5	bagus sekali	1	17	0.0	[bagus, sekali]
2647	Menurut saya aplikasi ini sudah oke untuk pemb...	5	menurut saya aplikasi ini sudah oke untuk pemb...	1	60	0.0	[menurut, saya, aplikasi, ini, sudah, oke, unt...

Figure 4 Tokenizing a Dataset

The final stage is removing words that have no effect and the removal of affixes in words.

	content	score	cleaned_text	label	content_len	punct	tokens	lemmatised_review
2651	Menjadi yang pertama itu sangatlah baik	5	menjadi yang pertama itu sangatlah baik	1	34	0.0	[menjadi, yang, pertama, itu, sangatlah, baik]	menjadi yang pertama itu sangatlah baik
2650	Next geoglee in blockchain ..... Barvo cryto 😊...	5	next geoglee in blockchain barvo cryto ...	1	46	10.9	[next, geoglee, in, blockchain, barvo, cryto]	next geoglee blockchain barvo cryto
2649	Nice app	5	nice app	1	7	0.0	[nice, app]	nice app
2648	Bagus sekali 👍👍👍👍👍👍	5	bagus sekali	1	17	0.0	[bagus, sekali]	bagus sekali
2647	Menurut saya aplikasi ini sudah oke untuk pemb...	5	menurut saya aplikasi ini sudah oke untuk pemb...	1	80	0.0	[menurut, saya, aplikasi, ini, sudah, oke, unt...	menurut saya aplikasi ini sudah oke untuk pemb...

Figure 5 Stopword Removal and Stemming

Researchers conducted sentiment analysis using Google Colab and Python programming language. The study was conducted on 2652 data, with 2326 data labelled as positive (87.71%) and 326 as negative (12.29%). Researchers divided the data into training data as much as 70% (1,856 reviews) and testing data as much as 30% (796 reviews).

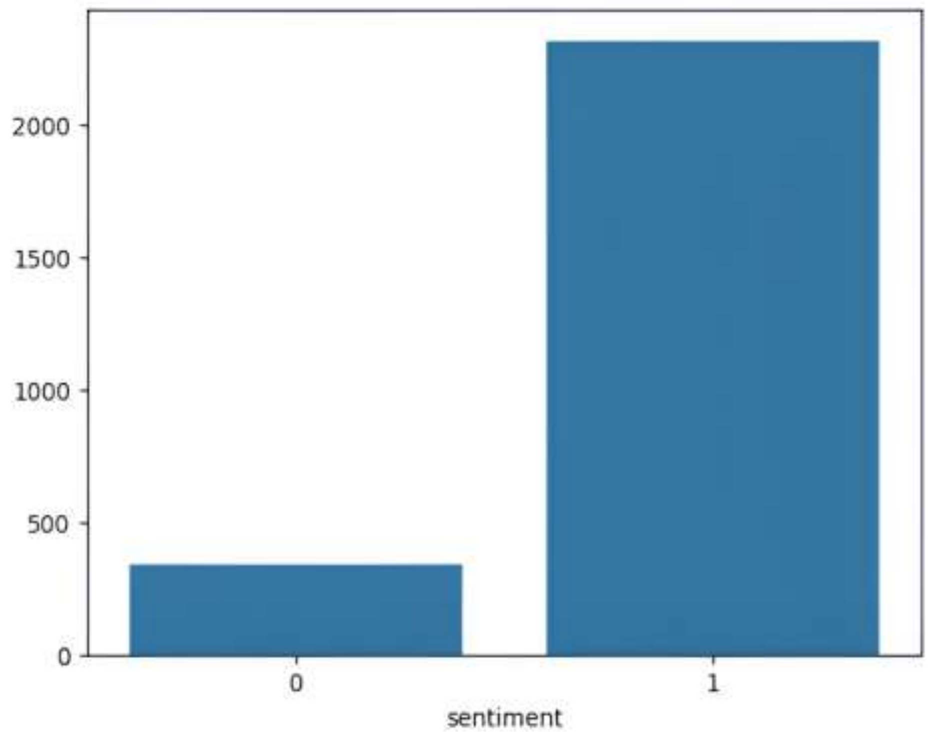

Figure 6 Sentiment chart before in SMOTE

An imbalance in the amount of data between positive reviews and negative reviews can result in an imbalance of data that can lead to errors in classifying minority classes that tend to be majority classes. Therefore, researchers use oversampling to balance data by adding data in minority classes. One of the oversampling methods used is the Synthetic Minority Oversampling Technique (SMOTE), which deals with unbalanced data problems or overfitting problems (Utami, 2022).

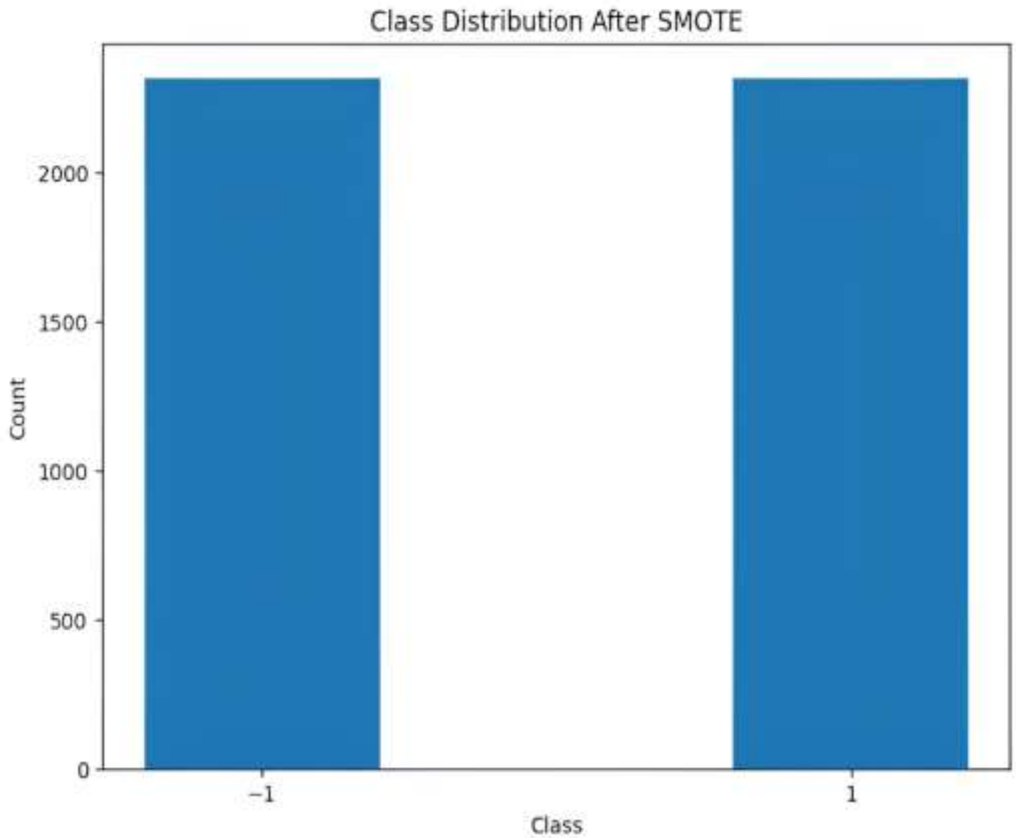

Figure 7 Sentiment Chart after in SMOTE

Figure 7 is a form of the dataset that has been in SMOTE by obtaining a balanced amount of data, namely 2326 positive and 2326 negative data. After that, researchers enter the data into each classification algorithm and get the following results.

Random Forest

Table 1
Random Forest melalui Confusion Matrix

	Negative	Positive
Negative	31	63
Positive	6	696

Researchers used the Scikit-Learn library to apply Random Forest classification to data. The analysis showed that out of 796 cases predicted to be positive, 696 (or 87.43%) were completely positive (True Positive), indicating that the model had high accuracy in identifying positive cases. In addition, of the 796 instances predicted negative, 31 (or 3.89%) were negative (True Negative), illustrating the model's ability to identify negative instances correctly. On the other hand, 63 cases (7.91%) were incorrectly predicted as positive when, in fact, they were negative (False Positive), indicating an error in classifying these cases. In comparison, only 6 cases (0.75%) were incorrectly predicted as negative when they were positive (False Negative), indicating that the model may tend to ignore some positive cases (Oktavia, Ramadahan, & Minarto, 2023).

Table 2
Results with Random Forest

	Precision	Recall
Negative	0.84	0.33
Positive	0.92	0.99
Accuracy: 0.91		
F1-Score: 0.90		

Table 2 shows the results of classification using the random forest algorithm. 91% accuracy indicates how well the model classifies all data correctly. The 90% F1-score is a combined measure of precision and recall, with a precision class negative of 84% and a precision class positive of 92%, describing the model's accuracy in classifying each class. Meanwhile, recall class negative reached 33% and recall class positive reached 99%, indicating the model's ability to identify negative and positive sentiments specifically. These results show that the recall value of the positive class is much higher than that of the recall class negative, indicating that the model is superior in recognising and classifying positive sentiment (Dey, Chakraborty, Biswas, Bose, & Tiwari, 2016).

Support Vector Machine

Table 3
Support Vector Machine melalui Confusion Matrix

	Negative	Positive
Negative	34	60
Positive	11	691

Researchers used the Scikit-Learn library to apply Support Vector Machine classification to data. The results indicate that out of 796 cases predicted to be positive, 691 (or 86.80%) are positive (True Positive), demonstrating the model's accuracy in identifying positive cases. In addition, of the 796 cases predicted to be negative, 34 (or 4.27%) were negative, illustrating the model's ability to identify negative instances correctly. On the other hand, 60 cases (7.53%) were incorrectly predicted as positive when they were negative (False Positive), indicating an error in classifying these cases. In comparison, only 11 cases (1.38%) were incorrectly predicted as negative when positive (False Negative), indicating that the model may ignore some positive cases.

Table 4
Results with Support Vector Machine

	Precision	Recall
Negative	0.76	0.36
Positive	0.92	0.98
Accuracy: 0.91		
F1-Score: 0.90		

Table 4 shows the classification results using the support vector machine algorithm. 91% accuracy indicates how well the model classifies all data correctly. The 90% F1-score is a combined measure of precision and recall, with a precision class negative of 76% and a precision class positive of 92%, reflecting the model's accuracy in classifying each class. Meanwhile, recall class negative reached 36% and recall class positive reached 98%, demonstrating the model's ability to identify negative and positive sentiments specifically. A higher positive class recall value than negative class recall indicates that the dominant model can recognise and classify positive sentiment well.

Naïve Bayes Classifier

Table 5
Naïve Bayes through the Confusion Matrix

	Negative	Positive
Negative	16	78
Positive	1	701

Researchers used the Scikit-Learn library to implement the classification of Naïve Bayes with Multinomial Naïve Bayes types, specifically designed for multinomial distributions such as text data represented in the form of TF-IDF. The analysis showed that of the total 796 data predicted positive, as many as 701 (or 88.06%) were True Positive (TP), illustrating the model's ability to identify positive cases correctly. In addition, out of a total of 796 data predicted to be negative, only 16 (or 2.01%) were True Negative (TN), demonstrating the model's ability to classify negative cases correctly. However, there were 78 data (or 9.79%) that were incorrectly predicted as positive when in fact they were negative (False Positive), and only 1 data (or 0.12%) was incorrectly predicted as negative when in fact it was positive (False Negative), indicating some errors in classification.

Table 6
Results with Naïve Bayes

	Precision	Recall
Negative	0.94	0.17
Positive	0.90	1.00
Accuracy: 0.90		
F1-Score: 0.87		

Table 6 shows the results of classification with the naïve Bayes algorithm. 90% accuracy indicates how well the model classifies all data correctly. The 87% F1-score is a combined measure of precision and recall, with a precision class negative of 94% and a precision class positive of 90%, illustrating the model's accuracy in classifying each class. Meanwhile, recall class negative reached 17% and recall class positive reached 100%, indicating the model's ability to identify negative and positive sentiments specifically. A positive recall class value that achieves a perfect score suggests that the dominant model can recognise and classify positive sentiments well.

The following is a combination of the results of each algorithm classification regarding the sentiment data analysis method that has been carried out.

Table 7
Overall algorithm classification results

Algoritma	Accuracy	Positive		Negative		Confusion Matrix				F1-Score
		Precision	Recall	Precision	Recall	TP	FN	FP	TN	
Random Forest	91 %	92%	99%	84%	33%	696	31	63	6	90%
Support Vector Machine	91 %	92%	98%	76%	36%	691	34	60	11	90%
Naïve Bayes	90 %	90%	100 %	94%	17%	701	16	78	1	87%

Word Cloud

A word cloud is a visual representation of text, where the font size signifies how often the word appears. Here is a word cloud that visualises data with their respective sentiment labels. Figure 10 shows a word cloud with a positive sentiment, while Figure 11 shows a negative sentiment.

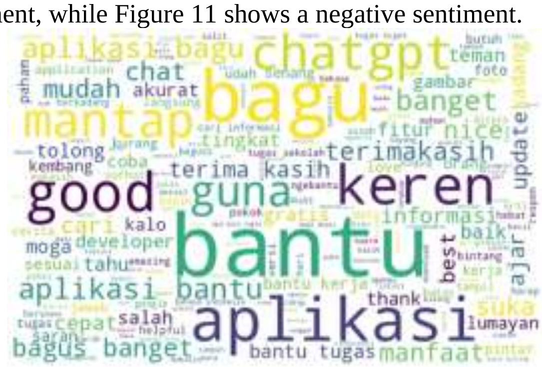

Figure 10 Positive Word Cloud

Figure 11 Negative Word Cloud

Figure 10 shows words that show positive sentiment results, such as the words "help", "good", "cool", "good", "thank you", "steady", "accurate", which means that most positive reviews are interested in the launch of ChatGPT which is a new thing. Figure 11 shows the results of negative sentiments such as the words "please", "wrong", "error", "login", "accurate", "different", and "answer", which means there are several reviews that contain their dissatisfaction with the presence of ChatGPT (Farid, Enri, & Umaidah, 2021).

4. Conclusion

Based on this study, from a total of 2652 review data on ChatGPT performance from July 28, 2023, to January 28, 2024, it was found that as many as 2326 (87.71%) reviews were positive, while 326 (12.29%) reviews were negative. This shows that people tend to respond positively to using ChatGPT based on ratings on the Google Play Store. In this study, researchers used the f1-score as the best evaluation method because the data was imbalanced, and the f1-score was considered the best way to measure how well the model handled minority classes. Through the classification of three different algorithms using testing data as much as 796 (30%) from a total of 2652 reviews, it was found that Random Forest obtained an f1-score value of 90% with positive correct data of 87.43% and negative correct data of 0.75%, Support Vector Machine got an f1-score value of 90% with positive, accurate data of 86.80% and negative valid data of 0.13%. Naïve Bayes received an f1-score of 87% with positive correct data of 88.06% and negative correct data of 0.12%. The results show that the Naïve Bayes classification algorithm has analytical capabilities under the Support Vector Machine and Random Forest, which has the model's ability to handle data more accurately, thus giving an equally high f1-score value in this sentiment analysis. Overall, the community responded to the use of the ChatGPT application with positive responses. Based on the level of accuracy obtained, it is concluded that the public's response to the ChatGPT application tends to be positive, which is reflected in the many positive comments given to ChatGPT on the Google Play Store.

5. References

Adrian, Muhammad Rivza, Putra, Muhammad Papuandivitama, Rafialdy, Muhammad Hilman, & Rakhmawati, Nur Aini. (2021). Perbandingan Metode Klasifikasi Random Forest dan SVM Pada Analisis Sentimen PSBB. *Jurnal Informatika Upgris*, *7*(1). https://doi.org/10.26877/jiu.v7i1.7099

Dey, Lopamudra, Chakraborty, Sanjay, Biswas, Anuraag, Bose, Beepa, & Tiwari, Sweta. (2016). Sentiment analysis of review datasets using naive Bayes and k-nn classifier. *ArXiv Preprint ArXiv:1610.09982*.

Farid, Farid, Enri, Ultach, & Umaidah, Yuyun. (2021). Sistem Pendukung Keputusan Rekomendasi Topik Skripsi Menggunakan Naïve Bayes Classifier. *JOINTECS (Journal of Information Technology and Computer Science)*, *6*(1), 35–42.

Fernández-Gavilanes, Milagros, Álvarez-López, Tamara, Juncal-Martínez, Jonathan, Costa-Montenegro, Enrique, & González-Castaño, Francisco Javier. (2016). Unsupervised method for sentiment analysis in online texts. *Expert Systems with Applications*, *58*, 57–75.

Fitri, Evita. (2020). Analisis Sentimen Terhadap Aplikasi Ruangguru Menggunakan Algoritma Naive Bayes, Random Forest Dan Support Vector Machine. *Jurnal Transformatika*, *18*(1), 71–80. https://doi.org/10.26623/transformatika.v18i1.2317

Hasibuan, Ernianti, & Heriyanto, Elmo Allistair. (2022). Analisis Sentimen Pada Ulasan Aplikasi Amazon Shopping Di Google Play Store Menggunakan Naive Bayes Classifier. *Jurnal Teknik Dan Science*, *1*(3), 13–24. https://doi.org/10.56127/jts.v1i3.434

Klyueva, Irina. (2019). Improving the quality of the multiclass SVM classification based on feature engineering. *2019 1st International Conference on Control Systems, Mathematical Modelling, Automation and Energy Efficiency (SUMMA)*, 491–494. IEEE.

Muslimin, Muhammad, & Lusiana, Veronica. (2023). Analisis Sentimen Terhadap Kenaikan Harga Bahan Pokok Menggunakan Metode Naive Bayes Classifier. *JURNAL MEDIA INFORMATIKA BUDIDARMA*, *7*(3), 1200–1209.

Oktavia, Dea, Ramadahan, Yudhi Raymond, & Minarto, Minarto. (2023). Analisis Sentimen Terhadap Penerapan Sistem E-Tilang Pada Media Sosial Twitter Menggunakan Algoritma Support Vector Machine (SVM). *KLIK: Kajian Ilmiah Informatika Dan Komputer*, *4*(1), 407–417.

Prayoginingsih, Sila, & Kusumawardani, Renny Pradina. (2018). Klasifikasi Data Twitter Pelanggan Berdasarkan Kategori myTelkomsel Menggunakan Metode Support Vector Machine (SVM). *Jurnal Sisfo*, *7*(02), 83–98.

Ratnawati, Luthfiana, & Sulistyaningrum, Dwi Ratna. (2020). Penerapan random forest untuk mengukur tingkat keparahan penyakit pada daun apel. *Jurnal Sains Dan Seni ITS*, *8*(2), A71–A77.

Rifaldi, Muhamad Ilmar, Ramadhan, Yudhi Raymond, & Jaelani, Irsan. (2023). Analisis Sentimen Terhadap Aplikasi Chatgpt Pada Twitter Menggunakan Algoritma Naïve Bayes. *J-SAKTI (Jurnal Sains Komputer Dan Informatika)*, *7*(2), 802–814. https://doi.org/10.30645/j-sakti.v7i2.687

Setiawan, Adi, & Luthfiyani, Ulfah Khairiyah. (2023). Penggunaan ChatGPT untuk pendidikan di era education 4.0: Usulan inovasi meningkatkan keterampilan menulis. *JURNAL PETISI (Pendidikan Teknologi Informasi)*, *4*(1), 49–58.

Tuhuteru, Hennie, & Iriani, Ade. (2018). Analisis Sentimen Perusahaan Listrik Negara Cabang Ambon Menggunakan Metode Support Vector Machine dan Naive Bayes Classifier. *Jurnal Informatika: Jurnal Pengembangan IT*, *3*(3), 394–401.

Utami, Herni. (2022). Analisis Sentimen dari Aplikasi Shopee Indonesia Menggunakan Metode Recurrent Neural Network. *Indonesian Journal of Applied Statistics*, *5*(1), 31–38.