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Performance Comparison of Random Forest and XGBOOST Algorithms on E-Commerce App Sentiment Analysis

Laila Salsabila[1], Fatma Sari Hutagalung[2]
[1,2]Department of InformationTechnology, Universitas Muhammadiyah Sumatera Utara, Indonesia

ABSTRACT

The rapid advancement of digital technology has driven significant growth in e-commerce applications in Indonesia, with Shopee emerging as one of the leading platforms boasting millions of active users. User reviews on the Google Play Store serve as a crucial data source for sentiment analysis and evaluating the quality of app services. However, the sheer volume and linguistic complexity of these reviews demand efficient and accurate analytical methods. This study aims to compare the performance of the Random Forest and XGBoost algorithms in classifying the sentiment of Shopee user reviews. Review data were collected through web scraping from the Google Play Store and processed using several labelling, casefolding, cleaning, tokenizing, stopword removal, and stemming. Feature extraction was performed using the TF-IDF method, and the data were split into training and testing sets. Sentiment classification models were built using the Random Forest and XGBoost algorithms and evaluated based on accuracy, precision, recall, and F1-score metrics. The results of this study are expected to provide recommendations for the most effective algorithm for sentiment analysis in e-commerce applications and contribute to the development of services and further research in data mining and natural language processing.

Keyword : Random Forest; XGBoost; TF-IDF; Accuracy Metric; Precision; Recall; F1-score.

Corresponding Author:
Laila Salsabila
Department of Information Technology
Universitas Muhammadiyah Sumatera Utara
Jl. Kapten Mukhtar Basri No 3 Medan, 20238, Indonesia.
Email : shalsabila0610@gmail.com

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1. INTRODUCTION

Technological advancements have transformed various aspects of human life, including how people interact with digital services. One rapidly growing innovation is e-commerce applications, which allow users to shop online more easily. Shopee, as one of the largest e-commerce platforms in Indonesia, has millions of active users who provide reviews regarding their experiences using the app. User reviews on the Google Play Store are an important indicator in assessing app quality, both in terms of functionality, convenience, and user satisfaction with the services provided (Saputra et al., 2025).

Reviews provided by users on the Google Play Store reflect their real-life experiences using the Shopee app. These reviews not only contain positive assessments of features that facilitate transactions, but also negative assessments, such as complaints about technical issues, such as bugs, errors, or problems with the payment and delivery systems. The sheer volume of reviews often makes it difficult for app developers to manually analyze user sentiment. Furthermore, the complexity of language, such as the use of slang ("mantap", "gak nyampe"), and ambiguity in context can potentially lead to misclassification. The large volume of data and class imbalance (more positive or negative reviews) require robust algorithms to minimize bias in the analysis process. Therefore, a computational approach capable of efficiently managing large and diverse data is needed (Nurian et al., 2024).

Based on the above issues, sentiment analysis is needed to transform textual review data into strategic insights, such as identifying logistics issues or product quality. Review data is taken directly from the Google Playstore app and from Shopee app reviews, while adhering to Shopee's privacy policy and avoiding the use of users' personal information. Research shows that 70% of consumers consider reviews a crucial factor in purchasing decisions, making accurate sentiment classification fundamental to service improvement. Sentiment analysis is a computational process using Natural Language Processing (NLP) and machine learning to classify text into positive and negative categories. Algorithms like Random Forest work by building multiple decision trees (bagging) and combining the results to improve prediction accuracy. This algorithm is known for its resilience to overfitting and its ability to handle large amounts of data. Meanwhile, XGBoost optimizes results through an iterative gradient boosting technique. Previous studies have shown XGBoost to be 532% faster in data processing, while Random Forest is more stable on imbalanced datasets. However, both have similar accuracy (~95%) in classification (Budaya et al., 2024).

The output of this study is a sentiment classification model capable of distinguishing reviews into two main categories: positive and negative. This model was evaluated using several standard machine learning metrics, such as accuracy, precision, recall, and F1-score. Accuracy is used to measure the model's ability to correctly classify data. Precision and recall help assess the model's performance against specific classes, especially in cases of imbalanced data. F1-score is used as an overall metric that combines precision and recall for a more objective evaluation (Atmajaya et al., 2023).
The main text format consists of a flat left-right columns on A4 paper. The margin text from the left and top are 2.5cm, right and bottom are 2 cm. The manuscript is written in Microsoft Word, single space, Cambria 10pt and maximum 12 pages, which can be downloaded at the website.

This research seeks to improve the performance of sentiment analysis compared to methods used in previous research. One of the main approaches implemented is the use of the XGBoost algorithm, which has proven superior in various domains, particularly in machine learning-based classification tasks. XGBoost is known for its ability to handle large amounts of data, address overfitting through regularization, and utilize boosting techniques to improve model accuracy.

In addition to using XGBoost, this study also focused on preprocessing and feature extraction. Preprocessing included data cleaning, such as removing special characters, normalizing text, and eliminating stemming that doesn't significantly contribute to sentiment analysis. This approach is expected to significantly improve the model's accuracy and effectiveness in classifying sentiment compared to previous research.

2. RESEARCH METHOD/MATERIAL AND METHOD/LETERATURE REVIEW

A. Random Forest

Random Forest is an ensemble-based machine learning algorithm consisting of many decision trees. This algorithm works by combining predictions from multiple trees to improve accuracy and reduce overfitting (Kurniawan et al., 2024).

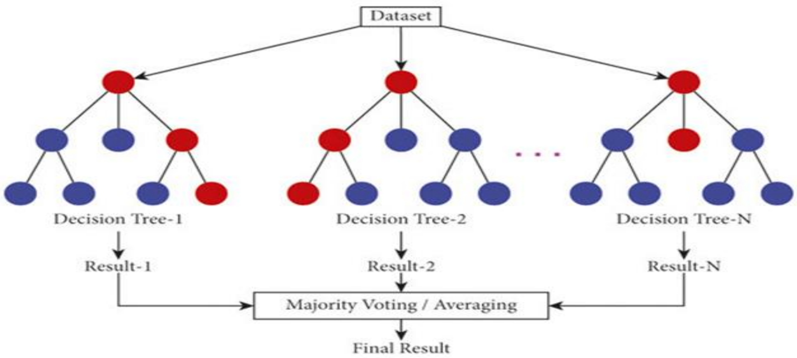

Fig 1. Random Forest Working Concept

B. XGBoost

XGBoost (Extreme Gradient Boosting) is a gradient-based boosting algorithm developed to improve the performance of machine learning models, particularly in data science competitions. This algorithm gradually optimizes decision trees by correcting prediction errors in previous iterations (Srinivas et al., 2021).

XGBoost's advantages over other methods are its robustness in training, its ability to handle imbalanced data, and its effectiveness in handling large numbers of features. However, its drawback is its higher model complexity compared to simpler algorithms like decision trees or logistic regression.

C. Data Preprocessing

The next stage after data collection is preprocessing. Briefly, this stage is carried out to process the data so that it is ready for use in subsequent stages. One of the steps performed is case-folding, which converts all text to lowercase to ensure there is no difference between words that have the same capitalization. Then, a cleaning process is carried out, which removes unnecessary characters or symbols, such as punctuation, numbers, and special characters that have no meaning in sentiment analysis. The next stage is tokenizing, which separates sentences into individual words.

After that, stopword removal is performed, which removes irrelevant words. Finally, stemming is performed to convert words to their base form. For example, the words "memakan" and "dimakan" are returned to their base form "makan." This preprocessing process makes the review data used in the study cleaner, more uniform, and ready for further processing in the feature extraction and sentiment classification stages (Yuyun et al., 2023).

D. Feature Extraction with TF-IDF

After the data is collected and processed, the next step is feature extraction using Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF is a technique used in text processing to convert text data into numeric representations. This technique works by calculating the weight of each word in a document based on how frequently the word appears in that document and how rarely it appears across the entire document collection. The more frequently a word appears in one document but rarely in another, the higher its weight.

The feature extraction process using TF-IDF begins with tokenization, which involves breaking down text into individual words. Each word is then weighted based on its frequency of occurrence within a given document and its relevance compared to other documents in the dataset. This process is automated using text processing libraries, such as scikit-learn, which can convert text into numeric vectors.

The application of TF-IDF in this study aims to capture the meaning of user reviews more effectively than simple methods like bag-of-words. With this weight-based representation, machine learning algorithms can more easily recognize emerging patterns in the data. Once the features are successfully extracted, the data, converted into numerical form, is ready for use in the data splitting stage for training a classification model.

3. RESULTS AND DISCUSSION

A. Data retrieval

Review data collection was performed using Google Colab scraping to obtain 500 reviews related to the Shopee app on the Google Play Store. The steps are as follows:

a. Get the URL directly from the Play Store https://play.google.com/store/apps/details?id=com.shopee.id&hl=id
b. Use the google_play_scraper library
c. Script to take comments
d. Saved review data

	userName	score	at	content
1	Jono Jendil	5	2025-07-18 08:02:54	top markotop sesuai pesanan
2	Ibnus Sibyan	5	2025-07-18 08:01:42	aplikasi yg sangat menguntungkan&sangat membantu jual beli. 👍👍👍👍
3	Umiyatul Fitri	5	2025-07-18 08:01:17	bagus dan pengiriman sangat cepat
4	Tamrin 1964	5	2025-07-18 08:01:15	sangat baik
5	Nanang Kurnia	5	2025-07-18 08:00:59	enak dan tidak mengecewakan klo dari shopee langsung
6	Muhammad Arsyad	1	2025-07-18 08:00:13	kurir shopee express nya kurang, ramah buruk
7	Yuli Posank	1	2025-07-18 07:59:56	ruh menghubungi penjual dan tidak bisa pembatalan pembeli merasa dirugikan sungguh sangat buruk sekali pelayanan shopee
8	Joko Purnomo	5	2025-07-18 07:59:33	.jozz selalu daah...
9	patan satriya	2	2025-07-18 07:58:34	voucher gjelas
10	Ramlah Mastura	5	2025-07-18 07:57:56	pesanan buku cepat datang
11	Mutiara	5	2025-07-18 07:57:13	bagus dan murah murah
12	Vipin Areska	1	2025-07-18 07:56:54	kembalikan uang refun saya,terlalu bertele2 nahan duit orang.
13	Rita Herlina	5	2025-07-18 07:56:35	s beli di shopee tuh bagus walau terkadang ada toko"tertentu yang g amanah semoga shopee lebih selektif lagi dalam bisnis ini
14	tito ito	5	2025-07-18 07:55:59	Pokoknya jossss
15	Wibowo Sudarman	5	2025-07-18 07:55:27	pesanan sesuai selalu,recomended deh
16	Ratna Nirfana	1	2025-07-18 07:55:09	terlalu bnyk verivikasi
17	Azka Kaza	5	2025-07-18 07:54:30	JOSJIIS
18	Lilis Sumiati	5	2025-07-18 07:54:22	makasih paket nya udah datang barang nya bagus
19	Henla Suhenla	5	2025-07-18 07:53:50	bagus harga bersahabat
20	Adi H	5	2025-07-18 07:53:41	senang belanja di shopee

Fig 2. Review Data

B. Sentiment Labeling Results

Sentiment labeling is based on the star rating provided by users, with the following conditions:

a. Positive Sentiment: If the rating is 4 stars or higher, the review is categorized as positive.
b. Neutral Sentiment: If the rating is 3 stars, the review is categorized as neutral.
c. Negative Sentiment: If the rating is 2 stars or lower, the review is categorized as negative.

	nama	rating	tanggal	komentar	sentimen
1	Jono Jendil	5	2025-07-18 08:02:54	top markotop sesuai pesanan	positif
2	Ibnus Sibyan	5	2025-07-18 08:01:42	aplikasi yg sangat menguntungkan&sangat membantu jual beli. 👍👍👍👍	positif
3	Umiyatul Fitri	5	2025-07-18 08:01:17	bagus dan pengiriman sangat cepat	positif
4	Tamrin 1964	5	2025-07-18 08:01:15	sangat baik	positif
5	Nanang Kurnia	5	2025-07-18 08:00:59	enak dan tidak mengecewakan klo dari shopee langsung	positif
6	Muhammad Arsyad	1	2025-07-18 08:00:13	kurir shopee express nya kurang, ramah buruk	negatif
7	Yuli Posank	1	2025-07-18 07:59:56	atalan pembeli merasa dirugikan sungguh sangat buruk sekali pelayanan shopee	negatif
8	Joko Purnomo	5	2025-07-18 07:59:33	.jozz selalu daah...	positif
9	patan satriya	2	2025-07-18 07:58:34	voucher gjelas	negatif
10	Ramlah Mastura	5	2025-07-18 07:57:56	pesanan buku cepat datang	positif
11	Mutiara	5	2025-07-18 07:57:13	bagus dan murah murah	positif
12	Vipin Areska	1	2025-07-18 07:56:54	kembalikan uang refun saya,terlalu bertele2 nahan duit orang.	negatif
13	Rita Herlina	5	2025-07-18 07:56:35	la toko"tertentu yang g amanah semoga shopee lebih selektif lagi dalam bisnis ini	positif
14	tito ito	5	2025-07-18 07:55:59	Pokoknya jossss	positif
15	Wibowo Sudarman	5	2025-07-18 07:55:27	pesanan sesuai selalu,recomended deh	positif
16	Ratna Nirfana	1	2025-07-18 07:55:09	terlalu bnyk verivikasi	negatif
17	Azka Kaza	5	2025-07-18 07:54:30	JOSJIIS	positif
18	Lilis Sumiati	5	2025-07-18 07:54:22	makasih paket nya udah datang barang nya bagus	positif
19	Henla Suhenla	5	2025-07-18 07:53:50	bagus harga bersahabat	positif
20	Adi H	5	2025-07-18 07:53:41	senang belanja di shopee	positif

Fig 3. Sentiment Labeling Results

C. Case-folding

After classifying sentiment, the next step is to carry out a case-folding process on some of the selected review data, where all letters are changed to lowercase.

	komentar
1	top markotop sesuai pesanan
2	aplikasi yg sangat menguntungkan&sangat membantu jual beli. 👍👍👍👍
3	bagus dan pengiriman sangat cepat
4	sangat baik
5	enak dan tidak mengecewakan klo dari shopee langsung
6	kurir shopee express nya kurang, ramah buruk
7	si gk ad respon, lapor shopee berkali-kali jawaban x itu itu saja suruh menghubungi penjual dan tidak bisa pembatalan pembeli merasa dirugikan sungguh sangat buruk sekali pelayanan shopee
8	.jozz selalu daah...
9	voucher gjelas
10	pesanan buku cepat datang
11	bagus dan murah murah
12	kembalikan uang refun saya,terlalu bertele2 nahan duit orang.
13	mayoritas beli di shopee tuh bagus walau terkadang ada toko"tertentu yang g amanah semoga shopee lebih selektif lagi dalam bisnis ini
14	pokoknya jossss
15	pesanan sesuai selalu,recomended deh
16	terlalu bnyk verivikasi
17	josjiis
18	makasih paket nya udah datang barang nya bagus
19	bagus harga bersahabat
20	senang belanja di shopee

Fig 4. Case-folding Results

D. Cleaning

After case-folding is done, the next stage is the cleaning process, where numbers, symbols, or punctuation marks will be cleaned.

	komentar
1	top markotop sesuai pesanan
2	aplikasi yg sangat menguntungkansangat membantu jual beli
3	bagus dan pengiriman sangat cepat
4	sangat baik
5	enak dan tidak mengecewakan klo dari shopee langsung
6	kurir shopee express nya kurang ramah buruk
7	isi gk ad respon lapor shopee berkalikali jawaban x itu itu saja suruh menghubungi penjual dan tidak bisa pembatalan pembeli merasa dirugikan sungguh sangat buruk sekali pelayanan shopee
8	jozz selalu daah
9	voucher gjelas
10	pesanan buku cepat datang
11	bagus dan murah murah
12	kembalikan uang refun sayaterlalu bertele nahan duit orang
13	mayoritas beli di shopee tuh bagus walau terkadang ada tokotertentu yang g amanah semoga shopee lebih selektif lagi dalam bisnis ini
14	pokoknya jossss
15	pesanan sesuai selalurecomended deh
16	terlalu bnyk verivikasi
17	josjiis
18	makasih paket nya udah datang barang nya bagus
19	bagus harga bersahabat
20	senang belanja di shopee

Fig 5. Cleaning Results

E. Stopword Removal

After tokenizing, the next stage is the stopword removal process, where words that do not contribute meaningfully to the analysis are removed.

	komentar
1	top markotop sesuai pesanan
2	aplikasi yg menguntungkansangat membantu jual beli
3	bagus pengiriman cepat
4	
5	enak mengecewakan klo shopee langsung
6	kurir shopee express nya ramah buruk
7	ya chat penjual ktx shopee mengembalikan dana chat ekspedisi gk ad respon lapor shopee berkalikali x suruh menghubungi penjual pembatalan pembeli dirugikan sungguh buruk pelayanan shopee
8	jozz daah
9	voucher gjelas
10	pesanan buku cepat
11	bagus murah murah
12	kembalikan uang refun sayaterlalu bertele nahan duit orang
13	mayoritas beli shopee tuh bagus terkadang tokotertentu g amanah semoga shopee selektif bisnis
14	pokoknya jossss
15	pesanan sesuai selalurecomended deh
16	bnyk verivikasi
17	josjiis
18	makasih paket nya udah barang nya bagus
19	bagus harga bersahabat
20	senang belanja shopee

Fig 6. Stopword Removal Results

F. Stemming

After stopword removal is carried out, the next stage is the stemming process, where words that have affixes are removed.

	komentar
1	top markotop sesuai pesanan
2	aplikasi yg menguntungkansangat membantu jual beli
3	bagu pengiriman cepat
4	
5	enak mengecewakan klo shope langsung
6	kurir shope express nya ramah buruk
7	rusak sya chat penjual ktx shope mengembalikan dana chat ekspedisi gk ad respon lapor shope berkalikali x suruh menghubungi penjual pembatalan pemb dirugikan sungguh buruk pelayanan shope
8	jozz daah
9	voucher gjela
10	pesanan buku cepat
11	bagu murah murah
12	kembalikan uang refun sayaterlalu bertel nahan duit orang
13	mayorita beli shope tuh bagu terkadang tokotertentu g amanah semoga shope selektif bisni
14	pokoknya jossss
15	pesanan sesuai selalurecomend deh
16	bnyk verivikasi
17	josjii
18	makasih paket nya udah barang nya bagu
19	bagu harga bersahabat
20	senang belanja shope

Fig 7. Stemming Results

G. TF-IDF

After the preprocessing stage is complete, the next step is feature extraction using TF-IDF (Term Frequency-Inverse Document Frequency), which converts text data into numeric values. Frequently occurring words will have a lower weight, while infrequent words will have a higher weight. The following is a list of frequently occurring and infrequent words, along with their weights:

Top 10 Kata dengan IDF Tertinggi (Paling Unik/Langka):

	Feature	IDF
0	abi	6.523459
1	nungguin	6.523459
2	ngelag	6.523459
3	ngerepotin	6.523459
4	ngga	6.523459
5	ngirim	6.523459
6	ngomong	6.523459
7	ngsih	6.523459
8	ni	6.523459
9	nice	6.523459

Top 10 Kata dengan IDF Terendah (Paling Umum):

	Feature	IDF
1121	sesuai	3.815409
1122	mantap	3.720099
1123	aplikasi	3.661258
1124	barang	3.579020
1125	yg	3.579020
1126	membantu	3.553044
1127	nya	3.553044
1128	belanja	3.105732
1129	bagu	2.899118
1130	shope	2.673311

Fig 8. TF-IDF Results

H. Data Splitting

After the TF-IDF stage is complete, the next stage is data splitting, where the data is divided into two parts: training data (80% of the total data) used to train the model, and test data (20% of the total data) used to test the model's performance. The following is the result of the data splitting:

```
Distribusi Sentimen di Data Latih (y_train):
sentimen
positif    331
negatif     61
netral       8
Name: count, dtype: int64

Distribusi Sentimen di Data Uji (y_test):
sentimen
positif    83
negatif    15
netral      2
Name: count, dtype: int64
```

Fig 9. Data Splitting Results

Based on the image above, the results of the data splitting show that the training data shows 331 positive data, 61 negative data, and 8 neutral data. The total training data is 400 data, corresponding to the division of 80% of the training data from the 500 existing data. The test data shows 83 positive data, 15 negative data, and 2 neutral data. The total test data is 100 data, corresponding to the division of 20% of the test data from the 500 existing data.

I. Data Classification

The next stage is data classification, where the data will be categorized into three classes: positive sentiment (2), neutral sentiment (1), and negative sentiment (0). The following are the results of the data classification:

```
Distribusi kelas di y_train:
2    331
0     61
1      8
Name: count, dtype: int64

Distribusi kelas di y_test:
2    83
0    15
1     2
Name: count, dtype: int64
```

Fig 10. Data Classification Results

After the data classification was completed, both models were trained with the script and the results were as follows:

```
# --- 8. Melatih Model ---

# Melatih model Random Forest
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_resampled, y_train_resampled)
print("\nModel Random Forest telah dilatih.")

# Melatih model XGBoost
xgb_model = XGBClassifier(eval_metric='mlogloss', random_state=42)
xgb_model.fit(X_train_resampled, y_train_resampled)
print("Model XGBoost telah dilatih.")
```

```
Model Random Forest telah dilatih.
Model XGBoost telah dilatih.
```

Fig 11. Training the Model

J. Confusion Matrix Results

After the Random Forest and XGBoost models are trained, several evaluation results, such as a Confusion Matrix, will appear. Here's what the Confusion Matrix from Random Forest and XGBoost looks like:

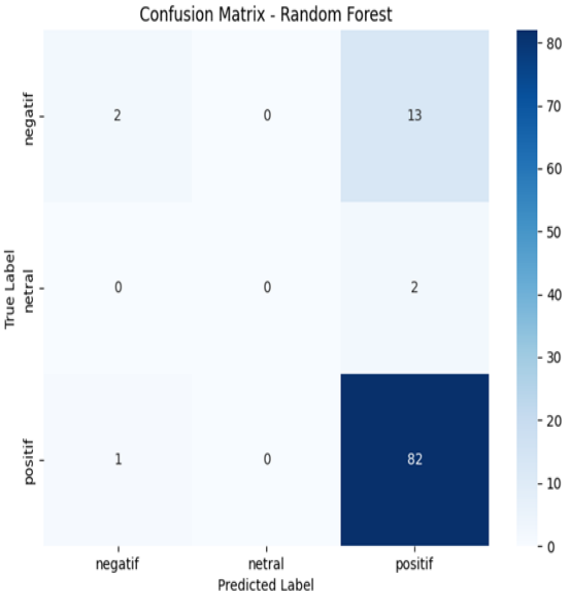

Fig 12. Confusion Matrix Random Forest

Table 1. Summary of Each Class in RF

Class	TP	FP	FN	TN
Negative	2	1	13	84
Neutral	0	0	2	98
Positive	82	15	1	2

Apart from that, there are also results from the XGBoost confusion matrix which will be attached as follows:

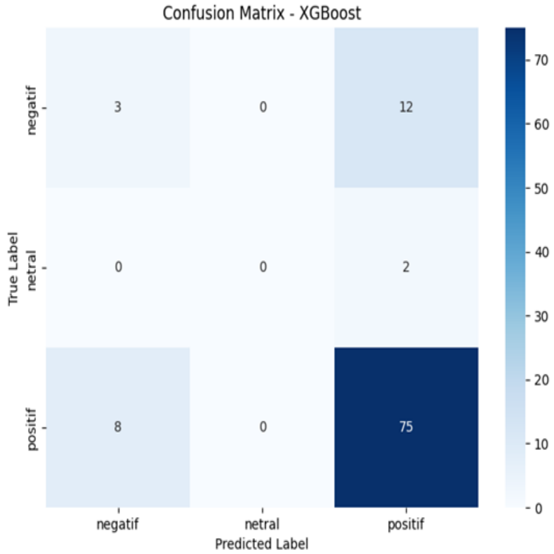

Fig 13. Confusion Matrix XGBoost

K. Classification Report Results

After the Confusion Matrix evaluation appears, the Classification Report results for both models will appear. Here's a look at the Classification Reports for Random Forest and XGBoost:

```
Classification Report - Random Forest:
              precision    recall  f1-score   support

     negatif       0.67      0.13      0.22        15
      netral       0.00      0.00      0.00         2
     positif       0.85      0.99      0.91        83

    accuracy                           0.84       100
   macro avg       0.50      0.37      0.38       100
weighted avg       0.80      0.84      0.79       100

Akurasi: 0.8400
```

Fig 14. Classification Report Random Forest

Based on the image above, the accuracy of the Random Forest model is 0.8400, or 84%. Manual calculations for each Random Forest Classification Report can be performed using the Random Forest Confusion Matrix.

Classification Report - XGBoost:

	precision	recall	f1-score	support
negatif	0.27	0.20	0.23	15
netral	0.00	0.00	0.00	2
positif	0.84	0.90	0.87	83
accuracy			0.78	100
macro avg	0.37	0.37	0.37	100
weighted avg	0.74	0.78	0.76	100

Akurasi: 0.7800

Fig 15. XGBoost Classification Report

Based on the image above, the accuracy of the XGBoost model is 0.7800, or 78%. Manual calculations for each XGBoost Classification Report can be performed using the XGBoost Confusion Matrix.

L. Pie Chart Results

After the Classification Report appears, a pie chart will appear showing the actual and predicted distributions of both models. Here's a pie chart showing the actual and predicted distributions of Random Forest and XGBoost:

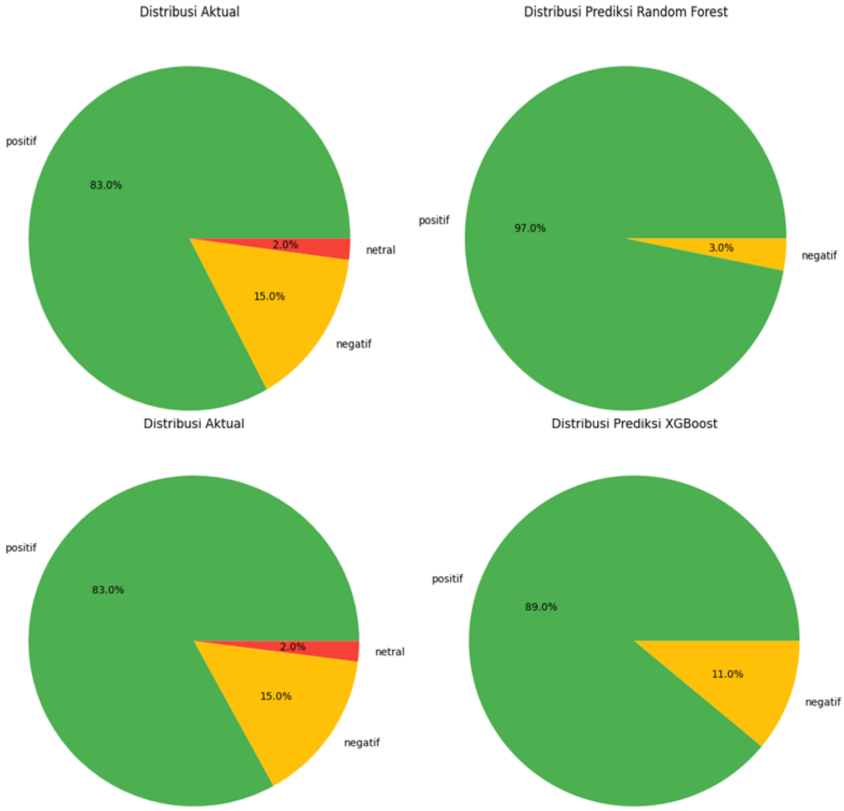

Fig 16. Pie Chart Results

Based on the pie charts of both Random Forest and XGBoost distributions, it can be concluded that both model predictions show an increase in the proportion of positive sentiment compared to the actual distribution, while the proportion of negative sentiment decreases and the neutral category disappears. This indicates that the models successfully recognize positive polarity but may be less sensitive in capturing neutral sentiment.

M. WordCloud Results

Fig 17. WordCloud Results

Based on the Word Cloud above, it can be concluded that both models demonstrate positive perceptions of Shopee, with an emphasis on ease of shopping and service efficiency. Despite some complaints, the majority of comments tend to be positive, indicating that Shopee has successfully met the expectations of many users. This analysis can serve as a reference for service improvements, particularly in terms of delivery and customer service response, to enhance user satisfaction.

4. CONCLUSION

The conclusion of the comparison of the Random Forest and XGBoost algorithms for sentiment analysis on the Shopee e-commerce application is as follows: Based on the research conducted, the implementation of the Random Forest and XGBoost algorithms for sentiment analysis of Shopee application reviews was carried out through several main stages. This begins with data collection, followed by data preprocessing, which consists of case-folding, converting all text to lowercase. Then, a cleaning process is carried out, removing unnecessary characters or symbols from the text. The next stage is tokenizing, separating sentences into individual words. Stopword removal is then performed, removing irrelevant words. Finally, stemming is carried out to convert words to their base form. This is followed by stemming, converting words with affixes to their base form. Feature extraction is then performed using TF-IDF, which converts text data into numbers based on their frequency of occurrence. Data separation and classification are then performed, and the algorithm model is trained using several metrics, such as accuracy, precision, recall, and f1-score. With these systematic steps, Random Forest and XGBoost can be effectively applied to analyze Shopee review sentiment. A comparison of the performance results between the Random Forest and XGBoost algorithms shows that the two algorithms have different accuracy values. The Random Forest algorithm obtained an accuracy of 0.8400 or 84%, while the XGBoost algorithm obtained an accuracy of 0.7800 or 78%.

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