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Sentiment Analysis of Alfagift Application User Reviews Using Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) Methods

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Abstract: The rapid advancement of mobile apps has emerged as an important aspect of the routine of internet-connected users. In Indonesia, many companies are introducing their apps to improve the quality of service for users, and Alfamart is one of them. However, users have identified many shortcomings in these apps. This feedback is provided by users on the review feature of the Alfagift app on the Google Play Store. This research aims to apply a sentiment analysis approach to identify the application's shortcomings so that developers can understand the aspects that need to be improved to improve the quality of application services. The research stages include data collection, preprocessing, labeling, weighting, classification of LSTM and SVM methods, and performance evaluation using a confusion matrix. The dataset consists of 1000 reviews obtained through web scraping techniques. This research uses the Lexicon-based method to classify the dataset into positive, negative, and neutral categories. The analysis results show that 801 data are classified as positive sentiment, 77 as negative sentiment, and 122 as neutral sentiment. Based on testing, both SVM and LSTM methods show good performance. The best accuracy results were obtained using the SVM method, which amounted to 83.5%. Meanwhile, the LSTM method achieved an accuracy of 82%.

Abstrak: Kemajuan pesat aplikasi mobile telah menjadi aspek penting dalam rutinitas pengguna yang terhubung dengan internet. Di Indonesia, banyak perusahaan yang memperkenalkan aplikasi mereka untuk meningkatkan kualitas layanan bagi pengguna, dan Alfamart adalah salah satunya. Namun, pengguna telah mengidentifikasi banyak kekurangan dalam aplikasi ini. Umpan balik ini disampaikan oleh pengguna melalui fitur ulasan pada aplikasi Alfagift di Google Play Store. Penelitian ini bertujuan untuk menerapkan pendekatan analisis sentimen guna mengidentifikasi kekurangan aplikasi sehingga pengembang dapat memahami aspek-aspek yang perlu diperbaiki untuk meningkatkan kualitas layanan aplikasi. Tahapan penelitian meliputi pengumpulan data, praproses, pelabelan, pembobotan, klasifikasi dengan metode LSTM dan SVM, serta evaluasi kinerja menggunakan matriks kebingungan. Dataset terdiri dari 1000 ulasan yang diperoleh melalui teknik web scraping. Penelitian ini menggunakan metode berbasis Lexicon untuk mengklasifikasikan dataset ke dalam kategori positif, negatif, dan netral. Hasil analisis menunjukkan bahwa 801 data diklasifikasikan sebagai sentimen positif, 77 sebagai sentimen negatif, dan 122 sebagai sentimen netral. Berdasarkan pengujian, baik metode SVM maupun LSTM menunjukkan kinerja yang baik. Hasil akurasi terbaik diperoleh dengan menggunakan metode SVM, yaitu sebesar 83,5%. Sementara itu, metode LSTM mencapai akurasi sebesar 82%.

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INTRODUCTION

In the modern era dominated by information technology, mobile apps play an important role in the lives of Indonesians, influencing many areas, including communication, entertainment, and online shopping (Hertayawan et al., 2023). The presence of apps makes access easier and more convenient and provides an opportunity to get a direct perspective from users through their reviews (Rahman et al., 2021). Because of this, many companies in Indonesia are launching specialized applications to get closer to customers and provide better services (Idris et al., 2023). One example is Alfamart with the Alfagift application. Alfagift is an e-commerce application available on the Google Play Store, designed to quickly and conveniently meet the shopping needs of Indonesian consumers (Harahap & Yuliana, 2022). More than 10 million people have downloaded the Alfagift app, and there are more than 277 thousand reviews on the Google Play Store. The Google Play Store platform provides various applications and other online products that can be downloaded for free or paid (Nashirudin, 2023). The review feature on the Google Play Store has the appeal to influence the decisions and perceptions of individuals considering the use of apps available on the platform (Daulay & Asror, 2020).

Through the Alfagift application, users can easily find various products and services offered by Alfagift (Perdana et al., 2022). However, behind this convenience are aspects that require consideration of user reviews to improve overall service quality. Therefore, companies can take advantage of the review feature function available in the Alfagift application in the Google Play store. In these reviews, various app users express praise, recommendations, criticisms, and even complaints (Estika et al., 2021). The large number of reviews poses a challenge regarding categorization and analysis. Therefore, an efficient method is needed to process these reviews quickly and accurately, making it possible to categorize the feedback into positive, negative, or neutral sentiments. Sentiment analysis proved to be an appropriate strategy for conducting this research. Sentiment analysis is a process that distinguishes the nature of opinions, categorized into positive, negative, or neutral sentiment classes. (Romadloni & Septiyanti, 2023).

Several previous studies have conducted sentiment analysis related to app user reviews, especially in e-commerce. The researcher (Idris et al., 2023) uses the SVM method to categorize comments on the Shopee application. The results showed that using the SVM method for classification gave good results, achieving an accuracy rate of 98%. A researcher (Rita, 2020) researched the Tokopedia application review using the Naïve Bayes method, dividing the dataset into training and test data. The training data contains 1000 comments, and the test data contains 1500 comments. The results of this study, the naïve Bayes method, obtained an accuracy rate of 97.13%, precision of 1%, and recall of 95.49%. Another study (Ahmadi et al., 2020) used the SVM method to conduct sentiment analysis on various online shop platforms on the Google Play Store, namely *Tokopedia JD.ID*, *Blibli*, *Shopee*, and *Lazada*. Among the various online shop platforms studied, the results show that Tokopedia achieved the highest accuracy rate of 90.67%. Other platforms, JD.ID at 75.33%, Blibli 74.00%, Shopee 70.00%, and Lazada 69.00%. Using the Stochastic Gradient Descent Algorithm method, researchers (Kurnia, 2023) conducted sentiment analysis on the Tokopedia and Shopee applications to determine user perceptions. The classification results show that Tokopedia has an accuracy value of 84%, precision of 87%, and recall of 90%, while Shopee has an accuracy value of 66%, precision of 65%, and recall of 66%. Graph-based and semi-supervised techniques were employed in research by (Chamid et al., 2023a), to enhance aspect-based sentiment analysis (ABSA). Aspect and opinion correlations are found using the GRN and

GCN techniques. Meanwhile, CNN and RNN methods are employed to enhance sentiment classification. The dataset used is a review of a marketplace. The aspect classification experiment results indicate that the best model was achieved using the GRN method, with an F1 score of 0.97144. In the sentiment classification experiment, the best model was achieved using the CNN method, with an F1 score of 0.94020. Research by (Chamid et al., 2023b) performed multi-label text classification on Indonesian marketplace user reviews using a Semi-Supervised Graph Neural Network. This research develops a Semi-Supervised Graph Neural Network (SSGNN) model for multi-label text classification. The evaluation results of the SSGNN model show an accuracy value of 0.861250, precision of 0.918303, recall of 0.918664, F1-score of 0.918484. In addition, the multi-label text classification results indicate that 8,777 aspects were correctly classified, whereas 2,492 aspects were incorrectly classified. Using the Cohen Kappa approach, researchers (Chamid et al., 2024) examined the consistency of multi-label data labeling for aspect and sentiment classification. This research uses data from scraping reviews of 4,307 Indonesian marketplace users. Based on the calculation results, the Kappa value is 0.909 for aspect detection, 0.893 for sentiment classification, and 0.971 for class aspects. From the outcomes of this study, labeled data that may be used for classification tasks, notably for aspect-based development, is acquired. The labeling results for aspect detection, sentiment classification, and aspect class are deemed "almost perfect" based on the high Kappa value.

This research aims to analyze user sentiment towards the Alfagift application and identify user reviews that are positive, negative, or neutral. The LSTM and SVM methods are used to compare the two methods' performance to determine which method provides the best results in sentiment analysis. The dataset was collected through web scraping of user reviews on the Google Play Store. After the data collection process, data preprocessing and sentiment labeling using the Lexicon-based method were performed. Next, data weighting is done using TF-IDF, and the system processes the data using LSTM and SVM methods. Performance evaluation uses a confusion matrix to provide an overview of the applied model's accuracy, precision, and recall (Adriana et al., 2023). This research takes on a strong sense of urgency from previous findings pointing to limitations in-app user evaluations and the importance of understanding user perceptions and preferences toward app services. This underscores the need for more in-depth and sophisticated research to explore how user reviews can impact service improvement. These findings highlight the need for new approaches in analyzing user reviews to inform more effective app service improvements that meet user needs.

The results of this research can constructively contribute by improving developers' understanding of user sentiment, thus offering valuable insights. This information helps developers know how users respond to the app, pinpoint areas that need improvement, and illustrate strengths and weaknesses in various aspects of the offering. Improved service quality has implications for user satisfaction and significantly affects the company's overall image.

METHOD

In order to increase the caliber of application services, this study evaluates user reviews of the Alfagift application with the highest level of accuracy possible using the LSTM and SVM algorithms. Figure 1 shows the stages of this research. This research begins with collecting datasets using web scrapping, and the data collection results go through a data preprocessing stage, which includes cleansing, case folding, tokenization, normalization, filtering, and stemming. Next, labeling is done using Lexicon Based to group the dataset into three classifications: positive, negative, and neutral, then weighting the words using TF-IDF. Classification is done with LSTM and SVM methods, and the last stage is the confusion matrix, which evaluates the results to obtain accuracy, precision, and recall values.

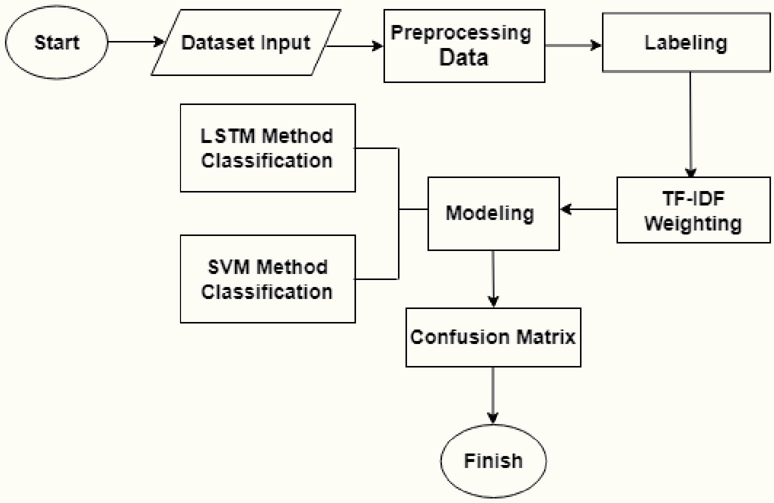

Figure 1. Research Phase

Data Collection

This data collection involved web scraping techniques, a process facilitated through programming in Python. The data collection procedure focuses on related categories, and the estimated timeframe for this data collection ranges from September to December 2023.

Data Preprocessing

The purpose of the data preprocessing step is to make the data simpler, ensure linguistic coherence, and eliminate irrelevant attributes that do not fit the research requirements (Aditiya et al., 2022). Preprocessing is a technique to convert raw text into usable information and is done in several stages, such as cleansing, case folding, tokenization, normalization, filtering, and stemming (Surbakti et al., 2021).

a. Cleaning: The cleaning process is the stage of data refinement, including the removal of characters that deviate from the specified criteria. (Furqan et al., 2022).
b. Case Folding: A systematic procedure that converts the entire text into a standardized format, specifically converting all letters to lowercase, such as changing the characters from "a" to "z" (Nurlaely et al., 2023).
c. Tokenization: Breaking text into small parts or "tokens", e.g., individual words or phrases (Nurlaely et al., 2023).
d. Normalization: The normalization process converts non-standard words into standard forms based on the KBBI dictionary reference (Adriana et al., 2023).
e. Filtering: The filtering process is an additional step to remove words containing redundant or unnecessary characters (Yuyun et al., 2021).
f. Stemming: A technique for converting words into their base form that removes the beginning and end of the word (Yuyun et al., 2021).

Data Labeling

Following the completion of preprocessing, the data must be labeled using lexicon-based, which produces three classifications, namely positive, negative, and neutral, by determining the score for each sentence first (Mahendrajaya et al., 2019). The score calculation results show that the sentence is categorized as a positive class if the score>0, categorized as a negative class if the score<0, and categorized as a neutral class if the score=0. The sentiment score can be calculated using Equation (1).

$$Score = (\sum positif\ words - \sum negatif\ words\ ) \tag{1}$$

The lexicon-based labeling approach is very important as it has many significant benefits. Firstly, this method does not require training data, which is very useful when it is difficult to obtain manually labeled data or if it is unavailable in sufficient quantity. By using the sentiment dictionary that has been developed, researchers can directly perform sentiment analysis without having to go through a time-consuming data labeling process. Secondly, this approach provides high interpretability and transparency, as each sentiment score assigned to a word or sentence can be traced back to the lexicon score used. This makes it easier for researchers to understand and explain the analysis results better.

TF-IDF Weighting

TF-IDF weighting is a technique that determines the relative importance of words or terms in a document (Melita et al., 2018). The frequency of a word's appearance in the document determines the TF-IDF value. Therefore, there is a direct correlation between the frequency of occurrence of a word in a document and the output of its association with that document; the greater the number of words, the higher the weight of the association. Conversely, the weight of the relationship between words in the document decreases when the number of words decreases (Septian et al., 2019). TF-IDF weighting consists of Term Frequency (TF) and Inverse Document Frequency (IDF). The TF-IDF weighting equation can be calculated using Equation (2). Where tf_d^t denotes the frequency of term t in document d. The total number of documents in each corpus is represented by the N variable., while df^t shows the number of documents that include t.

$$TF.IDF_{std}(t) = tf_d^t \ x \ log \frac{N}{df^t} \quad (2)$$

Classification Model

The classification model is carried out on the review data using the LSTM and SVM methods.

1. **LSTM**

LSTM is a Deep Learning method that can be applied across multiple domains in Natural Language Processing (NLP), covering tasks such as speech recognition, text translation, and sentiment analysis (Yahyadi & Latifah, 2022). The LSTM model is designed complexly, consisting of 4 components, namely forget gate, input gate, output gate, and memory cell, each of which plays an important role in the overall information processing (Widayat, 2021). The process starts with the forget gate stage, which is responsible for removing information that is deemed unimportant. This process is described in Equation (3).

$$ft = a(Wf \ \times \ [xt + ht - 1] + bf \quad (3)$$

Next, the information goes to the input fate to decide which data should be updated in the memory cell. This process is described in Equation (4). Then, the value in the memory cell is updated using Equation (5).

$$it = \sigma(w_i \times [xt + ht - 1] + b_i) \quad (4)$$

$$Ct = ft \times Ct - 1 + it \times C\ t \quad (5)$$

The last process occurs at the output gate, which produces the output and hidden state values important for sentiment classification, as represented by Equations (6) and (7).

$$ot = \sigma(Wo \times [xt + ht - 1] + bo \quad (6)$$

$$ht = ot \times \tanh(Ct) \quad (7)$$

After obtaining the output and hidden state values, sentiment classification can be calculated using sigmoid or softmax activation functions.

2. SVM

SVM is a machine learning algorithm based on data classification of data by identifying optimal separating lines (hyperplanes). This is achieved by optimizing the margin through a minimization process using the Lagrange technique (Fauzi, 2020). SVM has a strong theoretical foundation and a high classification accuracy rate compared to most other algorithms. The data classification process in SVM uses Equation (8). Where, the relationship between the input x and the resultant class is described by the *f(x)* variable. The weight vector w determines the direction of the hyperplane in the feature space, while the feature vector x represents the input data. The bias value b moves the hyperplane from its original position.

$$f(x) = w.x + b \tag{8}$$

Evaluation Model

The Confusion Matrix Method will be used to assess the model's performance as the final step in this study. Confusion matrix is used to measure the performance of the classification process and produces important matrices such as accuracy, precision, and recall (Styawati et al., 2021) (Romadhoni & Holle, 2022). A more comprehensive view of the model's performance, including the quantity of true positives, false positives, true negatives, and false negatives, is given by the confusion matrix, which also analyzes the model's strong and weak points.

Meanwhile, the F1 score presents an overall balance between precision and recall in one number. Detailed information about the model's performance is very important in this research, so the confusion matrix is used. Accuracy measures the proportion of accurate predictions, both positive and negative, compared to the entire data set (Ginantra et al., 2022) using Equation (9). The ratio of genuine positive predictions to total positive predictions is used to calculate precision (Ginantra et al., 2022) using Equation (10). Meanwhile, recall is defined as the ratio of properly predicted positive occurrences to the sum of correctly predicted negative events and correctly predicted positive events (Zusrotun et al., 2022) using Equation (11).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

$$Recall = \frac{TP}{TP+FN} \tag{11}$$

True positive (TP) indicates the proportion of instances in the class that are accurately identified. On the other hand, false positive (FP) is the condition where negative instances are wrongly called positive instances. False negative (FN) arises when an instance of the positive class is inaccurately identified as belonging to the negative class, and true negative (TN) indicates where an instance of the negative class is accurately identified.

RESULTS AND DISCUSSIONS

This research data was collected through web scraping from Alfagift application reviews. The dataset includes user reviews of the Alfagift application from September to December 2023. The dataset obtained amounted to 1000 review data. Table 1 is the result of web scraping, where the data extracted from the reviews is stored in CSV file format.

Table 1. Web Scrapping Results

Score	At	Content
5	12/22/2023	*Aplikasinya sangat bagus, bisa pesan online juga*
5	12/21/2023	*Aplikasi yg sangat membantu, belanja kebutuhan harian*
3	12/21/2023	*Produk sesuai*

…	…..	………
1	10/4/2023	*Aplikasinya oke, official store atau merchants nya yang*
3	9/27/2023	*Tolong untuk barang yg dikeranjang yang tidak diceklis*
2	9/16/2023	*Masih belum selancar dan sebagus indomaret*

Once the data collection stage is complete, processing cannot be done immediately due to considerable noise in the data set. Therefore, the preprocessing stage is an important part of data cleansing, aiming to remove irrelevant attributes at a later stage. The preprocessing stage includes cleansing, case folding, tokenization, normalization, filtering, and stemming. Table 2 shows the output of the data preprocessing stage.

Table 2. Preprocessing Result

Raw Data	
Apk nya sangat bagus 👍,mudah di jangkau, mempermudah belanja dan banyak promo menarik lainnya alfa gif mantap👌buat terus belanja di Alfagif 🥰	
Text Preprocessing	
Cleansing	*Apk nya sangat bagus mudah di jangkau mempermudah belanja dan banyak promo menarik lainnya alfa gif mantap*
Case Folding	*apk nya sangat bagus mudah di jangkau mempermudah belanja dan banyak promo menarik lainnya alfa gif mantap*
Tokenization	*apk,nya,sangat,bagus,mudah,di,jangkau,mempermudah,belanja,dan,banyak,promo,menarik,lainnya,alfa,gif,mantap*
Normalization	*apk,nya,sangat,bagus,mudah,di,jangkau,mempermudah,belanja,dan,banyak,promo,menarik,lainnya,alfa,gif,mantap*
Filtering	*apk,nya,bagus,mudah,jangkau,mempermudah,belanja,promo,menarik,alfa,gif,mantap*
Stemming	*apk,nya,bagus,mudah,jangkau,mudah,belanja,promo,tarik,alfa,gif,mantap*

Data that have undergone preliminary preprocessing is then labeled using a Lexicon-based dictionary. In the labeling process, the results of positive sentiment are 801 reviews, negative sentiment is 77, and neutral sentiment is 122 reviews. Table 3 displays the labeling process's outcomes.

Table 3. Labeling Result

Text_clean	**Score**	**Sentiment**
belanja alfagift mudah baby belanja barang lengkap disko bayar mudah pakai metode bayar mudah cepat pengirimanya sesuai jam rumah selamat belanja mudah cepat terimakasih sedia layan muas sukses	10	Positive
dapet poin belanja lumayan redeem barang mahal pas promo	0	Neutral
bayar aja susah ampun ujung pesan gagal pdahal apk nya bener kali aja nge bug udah update ubah bug bayar	-3	Negative

After the data labeling process, the information is further organized into groups to ascertain the frequency of the most frequently occurring words. These frequencies are then presented visually through word clouds. Each review is associated with a different set of words, whether categorized as positive, negative or neutral. "*Promos* (Promotion)", "*belanja* (shopping)", "*alfagift*", "*aplikasi* (app)", and "*sangat* (very)" are words frequently used in positive reviews, as shown in Figure 2.

Figure 2. Positive Word Cloud

Figure 3 shows that the words " *kecewa* (disappointed)", " *lambat* (slow)", "*susah* (difficult)", and " *batal* (canceled)" are the most commonly used words to give negative reviews.

Figure 3. Word Cloud Negative

Figure 4 shows that the words " *masuk* (login)", " *langsung* (direct)", " *pesan* (order)", " *toko* (shop)", and "voucher" are the most frequent in neutral reviews.

Figure 4. Word Cloud Neutral

TF-IDF extracts features using the Python library, which converts text features into vector representations and word grinding. Then, the data can be tested using LSTM and SVM classification. After the data is processed, the next step is to create a classification model using the LSTM and SVM techniques. The classification results of the LSTM method in Figure 5 show that the cumulative frequency of review data classified as positive sentiment is 199, while the cumulative frequency of neutral sentiment is 1.

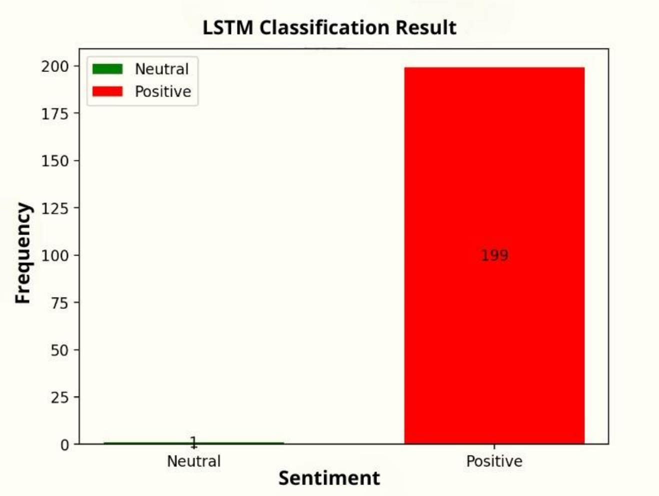

Figure 5. LSTM Classification Results

The SVM method's classification results are displayed in Figure 6. The results show that the total number of review data frequencies classified as positive sentiment is 187, negative sentiment is 2, and neutral sentiment is 11.

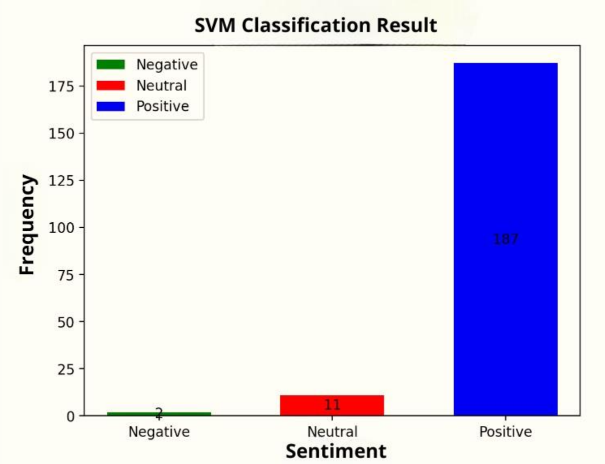

Figure 6. SVM Classification Results

After completing comprehensive data testing, the next stage involves conducting performance testing on the implemented model. This evaluation uses confusion matrices to obtain accuracy, precision, and recall values, as seen in Table 4.

Table 4. Confusion matrix result

Confusion matrix result				
	Accuracy	Precision	Recall	F1-Score
LSTM	82%	60%	35%	33%
SVM	83,5%	66%	44%,	47%

As shown by the confusion matrix results shown in Table 4, the SVM model shows better performance compared to the LSTM method. This advantage is due to the effectiveness of SVM in handling data with clear features and the fact that it can be separated linearly between classes (Cahyo & Aesyi, 2023). SVM models are better at overfitting, especially on small datasets, because SVM focuses on the maximum margin, which helps produce more generalized and stable models (Kristiyanti &

Hardani, 2023). The SVM algorithm produces a higher accuracy value of 83.5%, 66% precision, 44% recall, and 47% f1-score. On the other hand, the LSTM algorithm produces an accuracy value of 82%, precision of 60%, recall of 35%, and f1-score of 33%.

Figure 7 shows the results of analyzing the sentiment of Alfagift application users through the word cloud. This visualization provides a complete picture of the user reviews of the Alfagift application on the Google Play Store.

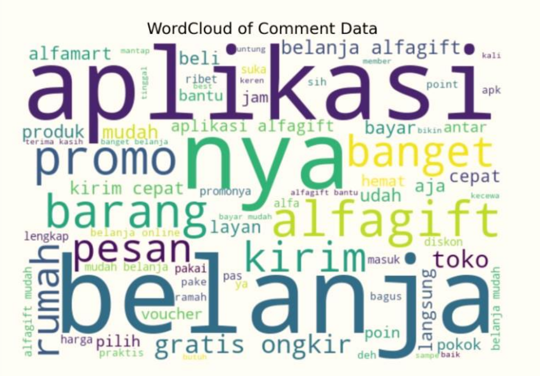

Figure 7. Word Cloud Data

CONCLUSIONS

Based on the research that has been done, it can be concluded that the sentiment observed from September to December 2023 from the Alfagift application reviews obtained a dataset of 1000 review data. There are 801 reviews of positive sentiment, 77 reviews of negative sentiment, and 122 reviews of neutral sentiment. This research uses the LSTM and SVM methods to analyze sentiment in Alfagift user reviews. The analysis results show that the SVM method has an accuracy value of 83.5%, a precision value of 66%, a recall value of 44%, and an f1-score value of 47%. In contrast, the LSTM method has an accuracy value of 82%, a precision value of 60%, a recall value of 35%, and an f1-score value of 33%. The test results show that the SVM method is better than the LSTM method. Recommendations for future research can focus on several aspects, including increasing the amount of data for model generalization, maintaining data balance between classes to avoid bias, and applying oversampling or undersampling techniques such as SMOTE to improve sentiment classification accuracy.

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