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SENTIMENT ANALYSIS OF E-GROCERY APPLICATION REVIEWS USING LEXICON-BASED AND SUPPORT VECTOR MACHINE

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Abstract
This research aims to conduct sentiment analysis of e-grocery application reviews using the Support Vector Machine (SVM) algorithm. Sentiment analysis is used to distinguish between positive and negative reviews by users who have provided reviews so that an evaluation of the services offered can be made. This research uses scraping techniques to obtain all the needed review data, focusing only on reviews of the Segari and Sayurbox applications. Datasets were collected from reviews using a library in Python, namely, google-play-scraper, obtained by the sayurbox application 4235 reviews and the segari application 5575. The dataset collected does not yet have a label, and the labeling process is impossible to perform manually by looking at the reviews one by one because it takes a long time and requires an expert in the field of language who can interpret the reviews and group them into positive and negative sentiments. Therefore, the sentiment-labeling process applies a lexicon-based method that works based on the inset lexicon dictionary by calculating each review's polarity value. The analysis process of this research uses the SVM algorithm because the SVM method has been proven to provide consistent and accurate results in various classification tasks, including sentiment analysis. The results show that the lexicon-based method and SVM produce good accuracy in determining the sentiment of e-grocery reviews, with a vegetable box application accuracy rate of 94%. In comparison, the segari application accuracy rate reached 97%.

Keywords: Sentiment Analysis; E-Grocery; Lexicon Based; Support Vector Machine (SVM); Application Reviews

Abstrak
Penelitian ini bertujuan untuk melakukan analisis sentimen ulasan aplikasi e-grocery menggunakan algoritma Support Vector Machine (SVM). Analisis sentimen digunakan untuk membedakan ulasan positif dan negatif dari pengguna yang sudah memberikan ulasan sehingga dapat dilakukan evaluasi terhadap layanan yang diberikan. Penelitian ini menggunakan teknik scraping untuk mendapatkan semua data ulasan yang dibutuhkan, dengan fokus hanya pada ulasan aplikasi segari dan aplikasi sayurbox. Dataset dikumpulkan dari ulasan menggunakan bantuan library pada python yaitu google-play-scraper, diperoleh aplikasi sayurbox 4235 ulasan dan aplikasi segari 5575. Dataset yang dikumpulkan belum memiliki label, proses pemberian label tidak mungkin dilakukan secara manual dengan melihat ulasan secara satu per satu karena membutuhkan waktu yang lama dan memerlukan seorang ahli di bidang bahasa yang dapat menafsirkan ulasan kemudian mengelompokkan ke sentimen positif dan negatif. Maka dari itu, proses pemberian label sentimen dengan menerapkan metode lexicon based yang bekerja berdasarkan kamus dari inset lexicon dengan menghitung nilai polariti dari setiap ulasan. Proses analisis penelitian ini menggunakan algoritma SVM, digunakan karena metode SVM terbukti memberikan hasil yang konsisten dan akurat dalam berbagai tugas klasifikasi termasuk analisis sentimen. Hasil penelitian menunjukkan bahwa metode lexicon based dan SVM menghasilkan akurasi yang baik dalam menentukan sentimen ulasan e-grocery dengan tingkat akurasi aplikasi sayurbox mencapai 94% sedangkan aplikasi segari tingkat akurasi mencapai 97%.

Kata kunci: Analisis Sentimen; E-Grocery; Lexicon Based; Support Vector Machine (SVM); Ulasan Aplikasi

INTRODUCTION

E-grocery is an online shopping service that allows consumers to order groceries and daily necessities online and receive home deliveries. The app will enable consumers to buy groceries quickly and efficiently without leaving their homes. Two popular e-grocery apps in Indonesia are Sayurbox and Segari. (Gandasari & Tjhin, 2024). Sayurbox and Segari offer convenience for consumers to obtain fresh products such as vegetables, fruits, meat, and other foodstuffs directly from local farmers and producers. These two applications help make it easier for consumers to shop and support farmers and small businesses by providing a platform to sell their products more widely. With the presence of Sayurbox and Segari, people can enjoy a more efficient and practical shopping experience and support environmental sustainability by reducing the carbon footprint generated by the distribution of food products. Thus, Sayurbox and Segari act as e-grocery service providers and catalysts for supporting the local economy and environmental sustainability. Both apps provide a modern solution to meet the food needs of busy urban communities while promoting healthier and more responsible consumption patterns. (Bakhar et al., 2023).

The rapid growth of e-grocery app users has resulted in many varied reviews regarding the user experience. These reviews contain valuable information that can be used to understand user perceptions of the services provided. Therefore, sentiment analysis of e-grocery app reviews is becoming increasingly important. Sentiment analysis is an automated process for identifying and categorizing opinions expressed in a text. It determines how a user reviews an app review by dividing the sentiment into two or more classes. Commonly used approaches in sentiment analysis are lexicon-based methods and Support Vector Machine (SVM) algorithms. At the same time, lexicons are crucial for sentiment analysis (Naldi & Petroni, 2023). This method is used for automatic labeling (Anggina, Setiawan, & Bachtiar, 2022) by utilizing a word dictionary (inset lexicon) (Manullang, Prianto, & Harani, 2023) that has been categorized based on positive and negative sentiments labeled with sentiments to identify polarity in the text (Nurkasanah & Hayaty, 2022a)(Musfiroh, Khaira, Utomo, & Suratno, 2021).

Additionally, integrating machine learning methods into lexicon-based approaches significantly enhances accuracy, surpassing pure lexicon-based methods (Eng, Ibn Nawab, & Shahiduzzaman, 2021) (Kumar & Pathak, 2022). InSet Lexicon, utilized for emotion recognition in Indonesian texts, is primarily a feature extraction dictionary focusing on sentiment and emotion analysis (Nurkasanah & Hayaty, 2022b). On the other hand, studies have shown the importance of lexicons in various contexts, such as climate change communication and sentiment analysis in different languages (Juanchich, Shepherd, & Sirota, 2020; Ozçelik et al., 2021). For instance, the creation and enrichment of affective lexicons, like the one for English-Spanish translations, play a crucial role in identifying emotional expressions in texts (Prinsloo, 2020).

The SVM algorithm, a robust machine learning algorithm, was used to classify the data based on the training of the labeled dataset. Previous research has shown that SVM, a machine learning model, can accurately classify sentiments (Diki Hendriyanto, Ridha, & Enri, 2022; Utami, Silvianti, & Masjkur, 2023).

This research explores the effectiveness of lexicon-based and SVM methods in analyzing the sentiment of e-grocery app reviews. Using these two approaches, we expect to find the most accurate and efficient method for categorizing user sentiment. In addition, the results of this sentiment analysis can be used to improve application performance and services for application developers and e-grocery service providers to improve service quality based on user reviews, maintain user trust, and strengthen competitive positions in an increasingly busy market. In addition, this study contributes to developing better and more effective public opinion sentiment analysis methods.

RESEARCH METHODS

The work stages are illustrated in Fig. 1. When we first perform the data collection stage, we need to install the Google Play store library to retrieve review data from Google Playstore. After collecting the data, we performed a preprocessing stage to convert the initial unstructured data into a more structured format, clean it, and prepare it for further analysis. The data from the scraping results do not yet have a label. The next stage is to label by utilizing a lexicon-based method to calculate the polarity value of a review so that it can be known that the review contains positive or negative words. Next, we divided the data into training and test datasets. We then explore the classification results of the model by looking for parameters for the best splitting data that produce the highest accuracy value and minimize model errors. Furthermore,

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based on the results of the best splitting parameters, the next step is modeling using the SVM algorithm by starting classification training and prediction in the test data step, which calculates and obtains the accuracy, precision, recall, and f1-score values. The last step is analyzing the results of each model, which can be represented in tabular form based on sentiment and represent world cloud visualization to find out the occurrence of words in e-grocery application reviews.

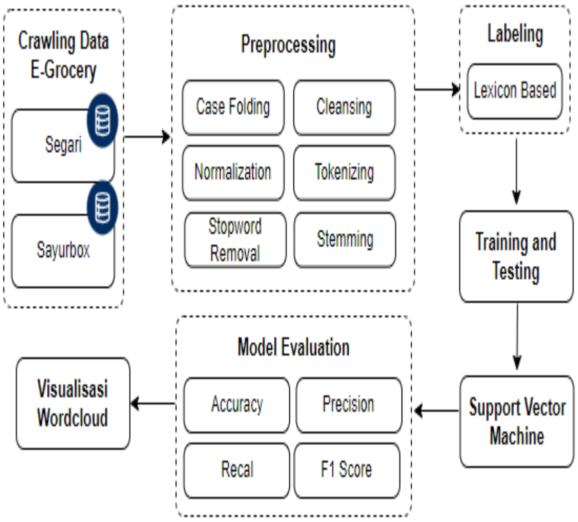

Figure 1. Research Method

Based on Figure 1. The stages of the data analysis in this study are as follows.

Crawling Data E-Grocery

The dataset is collected from the reviews from the Google Play store using web scraping techniques using Google Colab with the Python programming language and the Google-Play-Scraper library available in Python to retrieve data. The library is available in Python for data retrieval. The data used are secondary as a collection of user reviews from popular e-grocery Play Store applications in Indonesia, namely the Segari and Sayurbox applications.

Preprocessing

Preprocessing is essential in preparing the data before it is used in further analysis. The purpose of preprocessing is to clean the data from noise and errors, as well as transform the data into a structured form ready for processing. The preprocessing stages carried out in this study are:

a. Case Folding
   convert each letter in the review to lowercase (Ananda & Pristyanto, 2021; Hanafiah et al., 2023).
b. Cleansing
   Remove unnecessary components from the data (Munson, Smith, Boehmke, & Freels, 2019), such as links, hashtags, numbers, spaces, emojis, punctuation, and duplicate sentences.
c. Normalization
   Normalize short and non-standard words into standard words according to the KBBI (Sebastian & Nugraha, 2021).
d. Tokenizing
   Separates text into parts as tokens, chunks of letters, words, or sentences before further analysis (IŞIK & DAĞ, 2020).
e. Stopword Removal
   Remove meaningless words such as conjunctions utilizing the Natural Language Toolkit (NLTK) corpus library (Wang & Hu, 2021).
f. Stemming
   Remove the affixes on the word and make the word into the correct base word according to KBBI by utilizing the library in Phyton (Mustikasari, Widaningrum, Arifin, & Putri, 2021).

Labeling

Reviews are still unlabeled; therefore, it is difficult to determine whether a user provides a positive or negative review. It is impossible to perform the labeling process manually by looking at the reviews individually because it takes a long time [23] to interpret the reviews and categorize them into positive and negative sentiments. Therefore, labeling sentiment using a lexicon-based method is commonly known as a lexicon-based method. The dictionary used is the InSet Lexicon (Daffa et al., 2024) (Fernanda & Fathoni, 2024) (Anaba, Bagus Trianto, & Supriyadi, 2024), which consists of positive and negative dictionaries. The results of this process obtained data with 3820 positive sentiments, 718 negative sentiments, and 435 neutral sentiments from the sayurbox application. The data labeling process is presented in Table 1, which shows the sentiment class distribution of sayurbox app users.

Table 1. Sentiment Class Distribution of sayurbox App Users

	Sentiment	percentage
Positive	3820	77%
Negative	718	14%
Netral	435	9%

Table 2 shows the sentiment class distribution of segari app users. Labeling sentiment

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using a lexicon-based method is commonly known as a lexicon-based method. The results of this process obtained data with 2585 positive sentiments, 873 negative sentiments, and 404 neutral sentiments from the segari application. The data labeling process is presented in Table 2.

Table 2. Sentiment Class Distribution of Segari App Users

	Sentiment	percentage
Positive	2585	67%
Negative	873	23%
Netral	404	10%

Training and Testing

After the reviews are labeled, the next step is training and testing. Training is data used to calculate the probability of data based on the learning data carried out. In contrast, testing data is data that will or is happening and is used as test material previously obtained in the training data. This study uses a division of training data and testing data of as much as 80% and 20%, divided randomly (Aryanti et al., 2023).

Support Vector Machine

The support vector machine (SVM) is a powerful classification technique that aims to find the optimal hyperplane to separate two classes of data with the most significant margin (Adams, Farnell, & Story, 2020; Sukeiti & Surono, 2022). SVM is known for generalizing well and achieving high prediction accuracy (Mir & Nasiri, 2019). The hyperplane in SVM is the dividing line that separates the data points into different classes, with the points closest to the hyperplane being the support vectors (Fatin Liyana Mohd Rosely, Mohd Zain, Yusoff, & Yusup, 2019). These support vectors play a crucial role in determining the optimal hyperplane and are essential for the SVM's generalization properties (Hsu, Muthukumar, & Xu, 2021)

Model Evaluation

Evaluation is based on accuracy, precision, recall, and F1 score. Accuracy measures the extent to which a model correctly classifies data. It was calculated by dividing the correct predictions by the total number of predictions.

Visualization Wordcloud

Visualization is done by creating a word cloud that illustrates the frequency of terms that appear the most. Terms with large sizes are essential information in sentiment analysis.

RESULTS AND DISCUSSION

Sentiment analysis using lexicon-based and SVM on E-Grocery application reviews starts with crawling data using Python run on Google Colab with scrapping techniques from the Segari application obtained data as much as 5575 reviews, while from the Sayurbox application obtained data as much as 4235 reviews.

	userName	score	at	content
0	Pengguna Google	5	2024-06-05 16:28:58	packing rapih aman sayuran masih segar pengiri...
1	Pengguna Google	5	2024-06-03 12:46:48	Ok, barang nya pun fresh
2	Pengguna Google	1	2024-06-02 06:22:06	Masukin kode otp lwt wa sama SMS knp gk masuk2...
3	Pengguna Google	2	2024-06-02 02:21:07	Verifikasi cuman lewat Whatsapp,super2 lama ma...
4	Pengguna Google	5	2024-05-31 10:58:04	sayuran nya fresh banget mantap deh pokoknya

Figure 2. Sampe Data Segari

Figure 2 shows a sample of review data scraped from the Segari app.

	userName	score	at	content
0	Pengguna Google	5	2024-06-03 23:44:04	pengiriman cepat dan kualitas barangnya bagus
1	Pengguna Google	5	2024-06-03 03:54:14	Pengiriman tepat waktu, barang bagus, praktis
2	Pengguna Google	5	2024-05-27 03:39:59	Terimakasih atas bantuannya👍🏿
3	Pengguna Google	2	2024-05-22 07:55:45	payment nya cuma bisa pake astra pay? menurut ...
4	Pengguna Google	5	2024-05-17 12:50:58	mantap..

Figure 3. Sampel Data Sayurbox

Figure 3 shows a sample of review data scraped from the Sayurbox application. The scraped review data are then subjected to a text preprocessing stage to convert the initial unstructured data into a more structured format, clean it, and prepare it for further analysis. The main goal was to prepare data for practical use in machine-learning algorithms. The following preprocessing techniques will be used.

a. Case Folding

Change each letter in the review to lowercase. Table 3 below is the process before and after the data enters the case folding stage.

Table 3. Sample of Case Folding Process

Before	After
pengiriman cepat dan kualitas barangnya bagus	pengiriman cepat dan kualitas barangnya bagus
Terimakasih atas bantuannya 👍	terimakasih atas bantuannya 👍
Mendingan uninstall dah.. Promo vocer ga ada, kalaupun ada harus beli sayur 100 ribu dulu,promo bank	mendingan uninstall dah.. promo vocer ga ada, kalaupun ada harus beli sayur 100 ribu dulu,promo bank

Before	After
atau e walet juga syarat beli sayur 120k hadeh... Yg lebih parah lagi biaya penanganan 5500..	atau e walet juga syarat beli sayur 120k hadeh... Yg lebih parah lagi biaya penanganan 5500..
Seharus nya helpfull bgt tapi malah kebalikan nyaaaa	seharus nya helpfull bgt tapi malah kebalikan nyaaaa

b. Cleansing
To clean data through links, hashtags, numbers, whitespace, emojis, punctuation marks, and duplicate sentences. There is a need to eliminate 602 duplicate reviews from the segari app and 373 from the sayurbox app. Table 4 below is the process before and after the data enters the cleaning stage.

Table 4. Sample of Cleansing Process

Before	After
pengiriman cepat dan kualitas barangnya bagus	pengiriman cepat dan kualitas barangnya bagus
terimakasih atas bantuannya 👍	terimakasih atas bantuannya
mendingan uninstall dah.. promo vocer ga ada, kalaupun ada harus beli sayur 100 ribu dulu,promo bank atau e walet juga syarat beli sayur 120k hadeh... Yg lebih parah lagi biaya penanganan 5500..	mendingan uninstall dah promo vocer ga ada kalaupun ada harus beli sayur ribu dulu promo bank atau e walet juga syarat beli sayur k hadeh yg lebih parah lagi biaya penanganan
seharus nya helpfull bgt tapi malah kebalikan nyaaaa	seharus nya helpfull bgt tapi malah kebalikan nyaaa

c. Normalization
They are changing short and non-standard words into standard words according to the KBBI. Table 5 below is the process before and after the data enters the normalization stage.

Table 5. Sample of Normalization Process

Before	After
pengiriman cepat dan kualitas barangnya bagus	pengiriman cepat dan kualitas barangnya bagus
terimakasih atas bantuannya	terima kasih atas bantuannya
mendingan uninstall dah promo vocer ga ada kalaupun ada harus beli sayur ribu dulu promo bank atau e walet juga syarat beli sayur k hadeh yg lebih parah lagi biaya penanganan	mendingan uninstall sudah promo kupon tidak ada kalaupun ada harus beli sayuran ribu dahulu promo bank atau e walet juga syarat beli sayuran ke hadeh yang lebih parah lagi biaya penanganan
seharus nya helpfull bgt tapi malah kebalikan nyaaa	seharus nya membantu banget tapi bahkan kebalikan nyaa

d. Tokenizing
The tokenization stage breaks the entire content of the review text into pieces of words (termed words) that stand singly. Table 6, before and after being processed in the tokenization stage, contains the words that have been split up.

Table 6. Sample of Tokenizing Process

Before	After
pengiriman cepat dan kualitas barangnya bagus	['pengiriman', 'cepat', 'kualitas', 'barangnya', 'bagus']
terima kasih atas bantuannya	['terima', 'kasih', 'atas', 'bantuannya']
mendingan uninstall sudah promo kupon tidak ada kalaupun ada harus beli sayuran ribu dahulu promo bank atau e walet juga syarat beli sayuran ke hadeh yang lebih parah lagi biaya penanganan	['mendingan', 'uninstall', 'sudah', 'promo', 'kupon', 'tidak', 'kalaupun', 'harus', 'beli', 'sayuran', 'ribu', 'dahulu', 'promo', 'bank', 'atau', 'walet', 'juga', 'syarat', 'beli', 'sayuran', 'hadeh', 'yang', 'lebih', 'parah', 'lagi', 'biaya', 'penanganan']
seharus nya membantu banget tapi bahkan kebalikan nyaa	['seharus', 'membantu', 'banget', 'tapi', 'bahkan', 'kebalikan']

e. Stopword Removal
Removing words that have no meaning or words that have less meaning will affect the sentiment process, such as "and," "or," "in," and so on. Table 7 below shows the process of changing data before and after stopword removal is carried out.

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Table 7. Sample of Stopword Removal Process

Before	After
['pengiriman', 'cepat', 'kualitas', 'barangnya', 'bagus']	['pengiriman', 'cepat', 'kualitas', 'barangnya', 'bagus']
['terima', 'kasih', 'atas', 'bantuannya']	['terima', 'kasih', 'bantuannya']
['mendingan', 'uninstall', 'sudah', 'promo', 'kupon', 'tidak', 'kalaupun', 'harus', 'beli', 'sayuran', 'ribu', 'dahulu', 'promo', 'bank', 'atau', 'walet', 'juga', 'syarat', 'beli', 'sayuran', 'hadeh', 'yang', 'lebih', 'parah', 'lagi', 'biaya', 'penanganan']	['mendingan', 'uninstall', 'promo', 'kupon', 'beli', 'sayuran', 'ribu', 'promo', 'bank', 'walet', 'syarat', 'beli', 'sayuran', 'parah', 'biaya', 'penanganan']
['seharus', 'membantu', 'banget', 'tapi', 'bahkan', 'kebalikan']	['seharus', 'membantu', 'banget', 'kebalikan']

f. Stemming

All reviews are converted to their primary word forms or affixed at this stage. It aims to reduce variations in words with the same root. For example, they are converting "running", " running, and "run" into the "run." Table 8 shows the before and after stemming of the data.

Table 8. Sample of Stemming Process

Before	After
['pengiriman', 'cepat', 'kualitas', 'barangnya', 'bagus']	['kirim', 'cepat', 'kualitas', 'barang', 'bagus']
['terima', 'kasih', 'bantuannya']	['terima', 'kasih', 'bantu']
['mendingan', 'uninstall', 'promo', 'kupon', 'beli', 'sayuran', 'ribu', 'promo', 'bank', 'walet', 'syarat', 'beli', 'sayuran', 'hadeh', 'parah', 'biaya', 'penanganan']	['mending', 'uninstall', 'promo', 'kupon', 'beli', 'sayur', 'ribu', 'promo', 'bank', 'walet', 'syarat', 'beli', 'sayur', 'parah', 'biaya', 'tangan']
['seharus', 'membantu', 'banget', 'kebalikan', 'nyaa']	['harus', 'bantu', 'banget', 'balik', 'nyaa']

The results of text preprocessing leave 3,862 review data from the Sayurbox application and 4,973 review data from the Segari application. The next step is to continue with the sentiment class labeling stage with the lexicon-based method by utilizing the inset lexicon dictionary. Reviews were scored first by adjusting the words' weights in the dictionary. +5 for positive words and -5 for negative words. Subsequently, the review weights are summed and grouped into positive, negative, and neutral sentiments. Neutral was defined as the result of a review calculation worth 0. Because this analysis focuses only on positive and negative feelings, reviews containing neutral sentiments are eliminated. Thus, labeling results leave 3458 review data from the sayurbox application, Positive 2585, Negative 873, and 4,538 review data from the Segari application, Positive 3820, Negative 718. Table 9 shows the results of the labeling process.

Table 9. Sample of Lexicon-Based Labeling Process

Content	Value	Sentiment
pengiriman cepat dan kualitas barangnya bagus	4	Positive
Terimakasih atas bantuannya 👍	2	Positive
Mendingan uninstall dah.. Promo vocer ga ada, kalaupun ada harus beli sayur 100 ribu dulu,promo bank atau e walet juga syarat beli sayur 120k hadeh... Yg lebih parah lagi biaya penanganan 5500..	-2	Negative
Seharus nya helpfull bgt tapi malah kebalikan nyaaaa	-8	Negative

The next step after the reviews are labeled is training and testing. The data division in this study consisted of 80% training data and 20% testing data. Classification using the SVM algorithm. At this stage, researchers conducted trials to determine the parameters for the best splitting data that produced the highest accuracy value and minimized model-making prediction errors. The experimental results are presented in Tables 10 and 11, respectively.

Table 10. Experimental results to find the best parameters for the segari application

Test Size	Random State	Accuracy	Recall	Precision
0.1	0	0.95	0.98	0.96
0.1	5	0.97	0.99	0.97
0.1	10	0.96	0.99	0.96
0.1	15	0.94	0.97	0.96

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Test Size	Random State	Accuracy	Recall	Precision
0.1	20	0.97	1.00	0.97
0.1	**25**	**0.98**	**0.99**	**0.98**

Based on the experimental results in Table 10, the best test_size and random_state parameters, it was found that the test_size = 0.1 and random_state = 25 obtained higher accuracy, recall, and precision values than other sizes for the Segari application so that these sizes will be used to split the dataset.

Table 11. Experimental Results to Find the Best Parameters for Sayurbox Application

Test Size	Random State	Accuracy	Recall	Precision
0.1	0	0.92	0.97	0.93
0.1	5	0.91	0.98	0.91
0.1	**10**	**0.94**	**0.98**	**0.94**
0.1	15	0.94	0.98	0.93
0.1	20	0.93	0.96	0.95
0.1	25	0.93	0.98	0.94

Based on the experimental results in Table 11, the best test_size and random_state parameters obtained for the size of test_size = 0.1 and random_state = 10 obtained higher accuracy, recall, and precision values than other sizes for the sayurbox application. Therefore, this size was used to split the dataset. The SVM model was trained using split data with the testing parameters that were tested from the previous scenario.

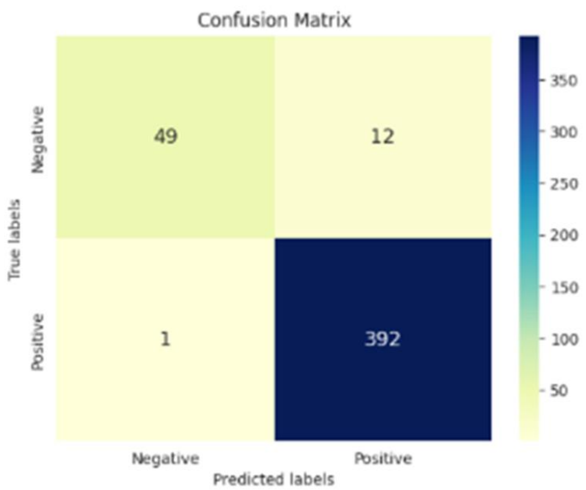

Figure 4. Confusion Matrix Segari

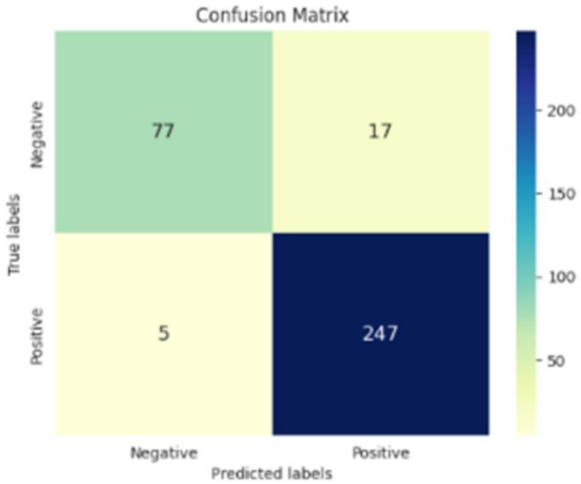

Figure 5. Confusion Matrix Sayurbox

The confusion matrix evaluation results were used to visualize the test results. They are depicted in Figures 4 and 5, respectively, and prove that the SVM model can perform sentiment analysis quite well.

```
              precision    recall  f1-score

    Negative       0.98      0.80      0.88
    Positive       0.97      1.00      0.98

    accuracy                           0.97
   macro avg       0.98      0.90      0.93
weighted avg       0.97      0.97      0.97
```

Figure 6. Sentiment Evaluation Results on the Segari App

```
              precision    recall  f1-score

    Negative       0.94      0.82      0.88
    Positive       0.94      0.98      0.96

    accuracy                           0.94
   macro avg       0.94      0.90      0.92
weighted avg       0.94      0.94      0.93
```

Figure 7. Sentiment Evaluation Results on Sayurbox app

Figure 6 and Figure 7 display a classification report that shows the results of evaluation metrics in detail.

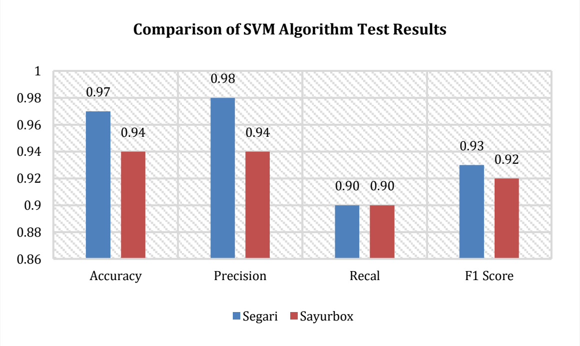

Figure 8. Comparison Chart of SVM Algorithm Testing Results

Graph 8 shows that the Segari application has higher accuracy results than the Sayurbox application. The accuracy rate reached 97%, the average precision value was 98%, the recall value was 90%, and the f1-score was 93%. The sayurbox application obtained an accuracy of 94%, an average precision value of 94%, a recall value of 90% and an f1-score of 92%. In addition, the segari application is more attractive than the sayurbox application, as evidenced by the many positive reviews visualized in Figure 9 and Figure 10.

Figure 8. Wordcloud for Segari app

Figure 9. Wordcloud for Sayurbox app

Based on the word cloud visualization displayed in Figure 8 is a visualization of the word from the Segari application review, where the word that often appears is the word fresh, with as many as 1158 words, shopping 1243 words, and promo 544 words. The visualization displayed in Figure 9 is a visualization of the Sayurbox application review, where the word that often appears is Sayurbox, as much as 723. Thus, it can be assumed that users are happy and like the service, delivery, quality, and price of the products provided by Segari and Sayurbox data.

CONCLUSIONS AND SUGGESTIONS

This study shows public opinion on E-Grocery applications based on data collected from Google Play Store reviews of Segari and Sayurbox applications. Based on the crawling results, 5575 reviews were obtained from the Segari application, while 4235 reviews were obtained from the Sayurbox application. For both applications, positive reviews were more common than negative reviews. We also used word clouds to categorize and find vocabulary or keywords often used in datasets describing the performance and user satisfaction of e-grocery applications. At delivery speed, fresh. In addition, determining the best parameters for splitting data can improve the performance of the SVM algorithm to produce the highest accuracy value and minimize model-making prediction errors. The best parameters of the Segari application were as follows: test_size = 0.1, random_state = 25, accuracy of 97%, average precision of 98%, recall of 90%, and the f1-score of 93%. The best parameters of the Sayurbox application were as follows: test_size = 0.1, random_state = 10, accuracy result of 94%, average precision value of 94%, recall value of 90%, and the f1-score of 92%. This sentiment analysis can be a foundation for further improvement and development of e-grocery applications, focusing on aspects that affect user satisfaction. The results show that the application of lexicon-based methods and SVM produces good accuracy in determining the sentiment of e-grocery reviews. In future research, we will apply different topics and techniques, such as algorithms, to obtain more accurate results in assessing public sentiment. These improvements are referenced in the body of this paper. In addition, by conducting this research, we can perform similar studies in the future with even better results and methodologies.

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