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Sentiment Analysis Classification of E-commerce User Reviews Using Natural Language Processing (NLP) and Support Vector Machine (SVM) Methods

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Abstract- In the swiftly changing digital age, e-commerce has become a vital component of everyday living. Individuals actively share product reviews, whether favorable or unfavorable, which companies can utilize to grasp users' views on their services. An efficient approach for evaluating and categorizing user sentiments is required to aid in analyzing these reviews. In this scenario, the Support Vector Machine (SVM) and Natural Language Processing (NLP) methods offer the appropriate answer. This research intends to develop a classification model capable of sorting e-commerce user feedback into positive, negative, or neutral sentiments. Utilizing NLP methods to analyze the review text and SVM as the classification approach, this model aims to achieve high accuracy in identifying user sentiment. Words that do not affect sentiment analysis, like "and," "that," "for," are eliminated, and SVM is utilized once the review data is converted into vectors via the TF-IDF method. The labeled sentiment training data will be used to train the SVM model.

Keywords: *E-Commerce, Natural Language Processing (NLP), Support Vector Machine (SVM).*

1. INTRODUCTION

E-commerce refers to the ability to conduct online transactions, including retail, online banking, and shopping, where buyers purchase goods and services [1]. The emergence of e-commerce is significantly beneficial for the sustainability of society. With e-commerce, consumers can make purchases 24 hours a day without needing to visit a store. Consumers can also view product and price information. Consumers can purchase products and services at lower costs by comparing various e-commerce platforms [2].

As the number of e-commerce platforms continues to grow, many users are providing reviews of their e-commerce applications. Based on analysis, the majority of users who install e-commerce applications also provide reviews of the applications they use. Reviews or ratings are important for new users who want to install e-commerce applications and determine which e-commerce application to use for transactions [3].

Technological advancements have changed customer behavior, leading to a preference for online purchases over in-person ones. This shift affects buyers’ decisions when it comes to purchasing products, and it is largely influenced by their perceptions of the marketing mix components: price, product, promotion, and place [4] Ratings are a component of reviews that use star symbols instead of text to convey user opinions. They can be viewed as an assessment of an application's ability to meet user preferences, reflecting the psychological and emotional states experienced during interaction with the app [5]. However, trust in these ratings can be undermined by inconsistencies in responses, such as reviews that feature negative comments alongside positive ratings. This discrepancy—where users give good ratings but write unfavorable reviews, or the reverse—can create confusion. Consequently, research is needed to find a reliable method to align user reviews with ratings. Ideally, ratings and reviews should correspond to help users choose e-commerce applications effectively [6]. The challenge addressed in this research is determining which texts or comments within e-commerce applications should be analyzed and visualized to derive meaningful rating values for the applications in question. This process of identifying relevant text within a database is known as text mining. Text mining involves extracting high-quality information from substantial textual data, with the goal of obtaining useful insights from a document [7].

Knowledge Discovery in Databases (KDD) is the process of extracting valuable information from large databases to gain new insights and support decision-making, commonly referred to as data mining. Data mining allows us to uncover hidden knowledge within databases, which can serve as a benchmark or guideline for analysis and action. The process of knowledge discovery in data mining typically involves several steps: dataset cleaning, data integration, data selection, data transformation, and data mining itself. Effective data mining requires appropriate algorithms and methods to convert input data into the desired output [8]. As a result, there are numerous algorithms tailored to various functions within data mining. For instance, algorithms used for classification can include statistical-based algorithms, distance-based algorithms, decision tree-based algorithms, neural network-based algorithms, and rule-based algorithms [9].

One of the algorithms that can be used to perform text mining analysis in conducting sentiment analysis of a product is the Support Vector Machine (SVM) method [10], SVM was created by Alexey Ya, Chervonenkis, and Vladimir N Vapnik in 1963, this algorithm is commonly used widely in image separation and classification problems, hypertext and text, SVM is one of the supervised model algorithms used for regression and classification to form an appropriate decision boundary or also called a hyperlane where the process separates n-dimensional space into several classes to make it easier to place points in the right group[11].

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2. RESEARCH METHODOLOGY

2.1 Text Mining

Text mining is a specialized field in data mining that involves mining text-based data, usually sourced from documents, and is used to search for words that represent the contents of a document as material for analyzing documents [12], grouping documents based on the words they contain, and finding relationships between documents and variables [13]. Text mining is a subset of data mining, the process of acquiring knowledge using analytical methods by interacting with a collection of documents over time [14].

Text mining is the discovery of knowledge in textual databases (KDT) [14]. Text mining is the process of extracting patterns in the form of previously unknown information and knowledge from a number of text data sources [15]. This type of input for text mining is called unstructured data and is the main difference from data mining, which uses structured data or databases as input. Text mining can be considered a two-stage process that begins with the application of structure to text data sources and continues with the extraction of relevant information and knowledge from the structured text data using the same techniques and tools as data mining. Common processes carried out by text mining include automatic summarization, document categorization, text clustering and others (Dharmawan, n.d).

2.2 Supervised Learning

Supervised learning is a method for grouping data objects into several classes. In supervised learning, each object in the data has features, which are characteristics inherent to each object. Each object in the data has the same number of features. These features are used as input to determine the object's class. In supervised learning, this is already known. Therefore, the problem faced in supervised learning is how to map objects into the correct class using the features each object possesses. Grouping in supervised learning is achieved by training to form a model. The classifier will then form a model that adapts to the features in the data. The resulting model can be a tree, a rule, or a function that can predict a class based on the features in the data. The next step is to validate the resulting model [16].

2.3 Sentiment Analysis

Sentiment is defined as an opinion or viewpoint referring to excessive feelings about something [12]. Sentiment Analysis is a technique for extracting information about opinions, sentiments, and emotions from text, which can include documents, product reviews, tweets, and so on. Sentiment and opinion are often used interchangeably, but they have fundamental differences. Sentiment is a feeling or emotion expressed by someone about something, such as positive, negative, and neutral. Opinion is a view expressed by someone about something, which can be positive or negative [11]. Sentiment analysis is an information mining technique that analyzes judgments, opinions, attitudes, behaviors, and emotions toward entities such as specific topics, services, products, and issues [17].

The primary goal of sentiment analysis is to determine the polarity of data. Therefore, the data analysis process, using classification, is used to predict whether data falls into the positive, negative, or neutral classes. There are three levels in sentiment analysis that serve as a reference for research: the document level, the sentence level, and the aspect level. The document level aims to classify an entire document into either the positive or negative class. For example, a sentiment analysis of public opinion toward a figure will yield positive or negative sentiment based on a single comment. The advantage of the document level is its ability to determine overall political significance [18].

2.3 Algoritma NLP and SVM

Natural Language Processing (NLP) is a branch of artificial intelligence that aims to process interactions between humans and machines through the use of natural language. In the context of sentiment analysis, NLP is used to extract, analyze, and classify information from unstructured text. One of the latest NLP models, BERT (Bidirectional Encoder Representations from Transformers), has demonstrated significant advantages in various sentiment analysis tasks. This advantage is based on its ability to understand context deeply and comprehensively. Sentiment analysis itself is closely related to Natural Language Processing (NLP), as it utilizes various NLP processing techniques aimed at understanding and classifying text based on its emotional expression. Furthermore, the application of machine learning models has the potential to improve sentiment prediction with a higher degree of accuracy [18].

Support Vector Machine (SVM) adalah salah satu algoritma yang digunakan untuk menetapkan batas-batas optimal antara kelas-kelas data, SVM digunakan untuk menemukan *hyperplane* terbaik dengan mengoptimalkan jarak antara kelompok data [19]. Dasar penerapan SVM adalah mengelompokkan informasi secara terpisah menggunakan *hyperplane* untuk meningkatkan margin diantara informasi tersebut, tujuannya untuk mencari fungsi klasifikasiyang paling sesuai dalam mengelompokan antara anggota dari dua kelas dalam data *traning*. [18].

2.3 Conceptual Framework

A conceptual framework is a framework for thinking that can be used as a problem-solving approach. Generally, this research framework uses a scientific approach and shows the relationships between variables in the analysis process.

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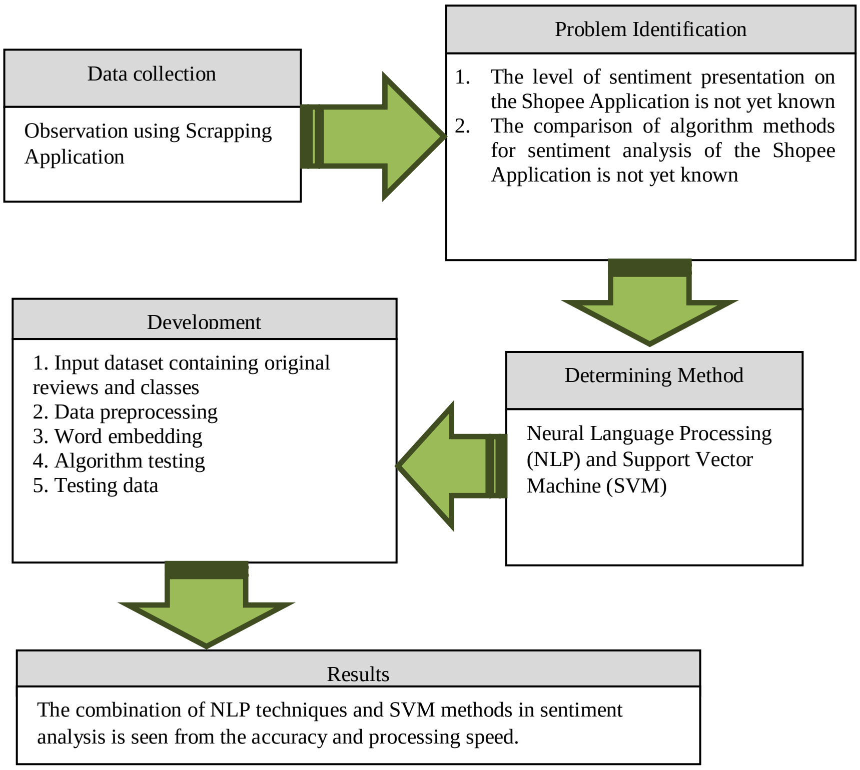

Figure 1. Conceptual Framework

3. RESULT AND DISCUSSION

According to John W. Tukey, data analysis is a procedure for analyzing data, techniques for interpreting the results of the analysis, and supported by a data collection process to make the analysis easier, more precise, and more accurate. Data analysis is also known as data processing or data interpretation. Data analysis is a series of activities to examine, group, systematize, interpret, and verify data so that a phenomenon has social, academic, and scientific value.

3.1 Data Analysis Technique

This study used web scraping techniques to collect data from Shopee e-commerce app reviews. The data collected were reviews from 2024. The results of the scraping of the research dataset are presented in the following figure. The dataset that went through the preprocessing step with and without NLP methods was divided into 2 parts with 200 training data and 50 test data. Then apply the load using the Term Inverse Frequency (TFIDF) algorithm. TF-IDF is used to weight the relationship between words or terms and the overall rating. The regularity of the appearance of a word in a review indicates the importance of the word in the review and which reviews contain those words so that reviews can be classified into 2 types (positive and negative reviews). Calculate TF-IDF using the following equation:

$$W_{x,y} = tf_{x,y} \times \log\left(\frac{N}{dfx}\right) \quad (1)$$

Where $Wx{,}y$ is the weight of the term (ty) against the document (dx). Meanwhile, $tfx{,}y$ is the number of occurrences of the term (ty) in the document (dx). N is the number of all documents in the dataset and dfx is the number of documents containing the term (ty), with at least one word being the term (ty).

Then, the results of the confusion matrix are calculated to obtain precision, accuracy, and recall values. Accuracy is the ratio of correctly classified samples to the total number of samples. Precision is calculated using Equation 2. Precision is the ratio of correctly classified positive samples to the total number of expected positive samples; precision is calculated using Equation 3. Article recall is the total number of correctly classified positive samples; recall is calculated using Equation 4.

$$Akurasi = \frac{TP+TN}{TP+FP+FN+TN} \quad (2)$$

$$Presisi = \frac{TP}{FP+TP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

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Equations 2, 3 and 4 are applied to the test results of two test data conditions, namely without the NLP approach and with the NLP approach.

3.2 Text Preprocessing

Shopee app user review data on the Google Play Store website is unstructured text data, so the text needs to be processed to obtain useful information. The stages carried out in this process are normalization, case folding, tokenizing, and stopwords. The first stage, or normalization, is a text process carried out to correct misspelled words or abbreviated words. For example, the word "tidak" can be written as "tdk, ngga, gak, engga," and many others. The spelling normalization process also translates foreign languages, especially English, into Indonesian. The normalization process can be seen in the following table.

Table 1. Proses Normalization

Input Data	Output Data
I absolutely love this app. So far, I haven't had any issues with returns or anything like that. Shopping on Shopee feels safe, shipping is super fast, there are lots of great events, and you can collect coins to exchange for discounts. Plus, I often get free shipping vouchers. Great job, Shopee!	"I absolutely love this app. So far, I haven't had any issues with returns or anything else. Shopping on Shopee feels safe, shipping is super fast, there are lots of great events, you can collect coins to exchange for discounts, and you often get free shipping vouchers. Shopee, great job!"

The second stage is case folding. Case folding is the process of converting all characters in a document to all uppercase or all lowercase to speed up comparisons during the indexing process. The case folding process is presented in the following table (Salam, Zeniarja, and Khasanah 2018).

Table 2. Proses Case Folging

Input Data	Output Data
I absolutely love this app. So far, I haven't had any issues with returns or anything like that. Shopping on Shopee feels safe, shipping is super fast, there are lots of great events, and you can collect coins to exchange for discounts. Plus, I often get free shipping vouchers. Great job, Shopee!	"I absolutely love this app. So far, I haven't had any issues with returns or anything else. Shopping on Shopee feels safe, shipping is super fast, there are lots of great events, you can collect coins to exchange for discounts, and you often get free shipping vouchers. Shopee, great job!"

Then, we move on to the third stage, tokenizing. Tokenizing is the process of separating text into word fragments called tokens. The goal of this process is to obtain word fragments that will become valuable entities in the text document matrix to be analyzed. Next, we move on to the final stage, stopwords. In this stage, words or symbols that do not provide useful information are eliminated (Utami 2017).

Table 3. Proses Stopword

Input Data	Output Data
I absolutely love this app. So far, I haven't had any issues with returns or anything like that. Shopping on Shopee feels safe, shipping is super fast, there are lots of exciting events, and you can collect coins to exchange for discounts. Plus, I often get free shipping vouchers. Good job, Shopee.	I like Aplication Fitur Return Goods Pieces Price Voucher Free Postage Delivery Safe Fast Profit

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3.3 Classification

Classifying review text using the NPL and Support Vector Machine algorithms on a dataset that has been preprocessed previously. Classification is done by dividing the dataset into two parts: the training dataset and the testing dataset. The classification results are carried out on 200 review data divided into 2 sentiment polarities, namely negative and positive sentiment and have been categorized into 4 aspect categories, namely service, on time, shipping, and price. Next, the classification results will be tested. The test aims to determine the performance of the classification model after passing the training stage. The training stage is carried out by dividing the review dataset into a 90:10 ratio where 90% of the dataset is training data and 10% of the dataset is test data. So the amount of test data is 50 review data. Then the training data will be trained using the NPL and Support Vector Machine algorithms.

The research was conducted through computer simulation using the SVM model. The following will briefly describe the basic idea of SVM. Suppose given a set X={x1, x2,…xm}, with Xi € Rn , i=1, …, m, it is known that X has a certain pattern, namely if xk is included in a class then xk is given a label (is the target) yk = -1. Thus the given data is in the form of pairs (x1, y1),…..,(xm, ym) € X x {+1,-1}. In learning problems, the collection of pairs is the SVM learning data. Armed with learning experience using the learning data, the SVM must be able to determine the pattern (generalization) of x € X.

$$X_n = \frac{0.8 * (X - a)}{b - a} + 0.1$$

Di mana :

X_n	=	Nilai ke – n
A	=	Nilai angka terendah
B	=	Nilai angka tertinggi
0.8 dan 0.1	=	Ketetapan

By using this equation, we can find the value of the data transformation x1(Attendance) and x2(Value).

Table 4. Klasifikasi

SENTIMENT	AMOUNT
POSITIF	154
NEGATIF	46

After obtaining the model results from the NLP and SVM classification machine learning models, a test scenario was conducted using four split test data. The resulting learning model was tested using new data that had not been previously trained.

Table 5. Contingency Table

Data Class	Class Prediction	
	+	-
+	Positive Value	False Negative
-	False Positives	Negative Value

The number of observation data in the positive category that can be predicted positively (correctly predicted) by machine learning is called True Positive (TP). True Negative (TN) is the total observation data in the negative class that can be predicted negatively (correctly predicted) by the machine learning algorithm. False Positive (FP) is the total observation data that is classified as positive but has a prediction error. False Negative (FN) is the number of observations that are classified as negative but have a prediction error.

1. Accuracy is the percentage of correct predictions. Accuracy is used as the accuracy between actual and predicted values.

$$Accuracy = \frac{True\ Positive + False\ Negatife}{TP + FP + TN + FN}$$

2. Precision evaluates the ability of an information retrieval system to retrieve the most relevant top-ranked data, and is defined as the percentage of returned data that is truly relevant to the user's query.

$$Precision\ = \frac{Relevan\ Document\ \pi\ Retrived\ Document}{Retrived\ Document}$$

3. Recall to find all relevant elements in data collection and is defined as the presentation of received data in relation to user requests.

$$Recall\ = \frac{Relevan\ Document\ \pi\ Retrived\ Document}{Retrived\ Document}$$

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Table 6. Data Set

NO	Date	User Name	Review	Reting	Sentimen
1	10/12/2024 02:15:00	User Google,1	At least many shops with a rating of *1 are blocked, okay?	3	Negative
2	10/12/2024 02:14:00	User Google,2	I wonder if I'm the only one here who has a SpayLater bill but I don't feel like I made that purchase... this is the third time... please ensure that your security is truly protected.	2	Negative
3	10/12/2024 02:12:00	User Google,3	Shopee is now slow, deliveries often have errors, and they often get lost. Ultimately, the package is returned to the store.	3	Negative
4	10/12/2024 02:11:00	User Google,4	Good	5	Positive
5	10/12/2024 02:10:00	User Google,5	Very helpful for online travel	5	Positive
6	10/12/2024 02:09:00	User Google,6	So far it is safe, fast and reliable	5	Positive
7	10/12/2024 02:08:00	User Google,7	I'm surprised by this online shopping app, how can I explain it? Every time I order COD payment, it arrives really fast, not according to the arrival date. When I order Shopee pay, it takes a really long time, even outside the arrival date.	3	Negatif
8	10/12/2024 02:07:00	User Google,8	good	5	Negative
9	10/12/2024 02:06:00	User Google,9	Good	5	Positive
...	......	......	....	....	....
...	......	......	....	....	....
...	......	......	....	....	....
200	10/12/2024 02:02:00	User Google,10	Nowadays shopee mostly cheats... before CO gets a cut, it's just right Once you choose the payment method, the deduction disappears..	3	Negative

3.4 Method Design

To better understand how this research works, several steps have been taken. In this section, the researchers divided the data into two parts: sample data, which includes fifty out of a total of 200 data points and five attributes. The classification stage of the Natural Language Processing (NLP) and Support Vector Machine algorithms involves training and testing. In this stage, the training process is first performed. After that, the testing process is carried out to evaluate the probability of the training dataset. The figure shows a flowchart of the classification stage of the algorithm.
This study conducted sentiment analysis using natural language processing on product reviews on Shopee. Sentiment analysis is an approach and technique used to analyze opinions, sentiments, and emotions contained in text. This method can be used to understand users' views on a topic, product, service, or brand. Natural Language Processing (NLP) is a branch of computer science and artificial intelligence that focuses on the understanding, processing, and generation of human language by computers. Furthermore, sentiment analysis was conducted using the Support Vector Machine algorithm to classify public opinion as positive, negative, or neutral.

The dataset that went through the preprocessing step with and without NLP methods was divided into 2 parts with 200 training data and 50 test data. Then apply the load using the Term Inverse Frequency (TFIDF) algorithm. TF-IDF is used to weight the relationship between words or terms and the overall rating. The regularity of the appearance of a word in a review indicates the importance of the word in the review and which reviews contain those words so that reviews can be classified into 2 types (positive and negative reviews). Calculate TF-IDF using the following equation:

$$Wx,y = tf\ x \log(\frac{n}{df})$$

Where Wx,y is the weight of the term (ty) against the document (dx). While tfx,y is the number of occurrences of the term (ty) in the document (dx). N is the number of all documents in the dataset and dfx is the number of documents containing the term (ty), with at least one word being the term (ty).

Table 7. Word Writing in Review 1

No	Writing Terms	Word Nomalization	Number of Reviews
1	blok	Block	11
2	yg	Wich	22
3	And2	Adges	5
4	How	How	4
5	yes	Iya	10

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6	Skrg	Now	17
7	can	Can	20
8	Lst	Lost	26
9	Already	Already	30
10	Okkkayy	Oke	2

The table above shows variations of words that have the same meaning. The word "block" was found in 11 reviews and the word "yg" was found in 22 reviews, used by buyers to replace the word "Ujung2" found in 5 reviews. The word "gimana" was found in 4 reviews and the word "yah" was found in 10 reviews used by buyers to replace the word "iya". The word "Skrg" was found in 17 reviews, the word "dpt" was found in 20 reviews, the word "ilang" was found in 26 reviews, the word "Udh" was found in 30 reviews, the word "Okkkayy" was found in 2 reviews. Using a word normalizer can handle variations of words that are often used in buyer review texts to turn them into similar terms. Next, the stemming process is carried out on the dataset, to remove prefixes, inserts, and suffixes so that words become basic forms, with the aim of making information retrieval easier and more efficient. An example of the application of stemming is shown in the table below.

Table 8. Stemming Implementation Process

No	Writing Terms	Stemming	Number of Reviews
1	Subscribe	Subscriber	8
2	Ordered	Message	2
3	Sent	Send	25
4	Send	Send	8
5	Cancel	Cancelled	14
6	Canceled	Cancelled	15
7	Shopping	Shopping	7
8	Spent	Shopping	26
9	Doing business	Business	21
10	Business	Business	11

In the table above, you can see words in the review such as "beluang" and "dibeluang". If removed, the prefix, infix, and suffix become the root word "dibeluang". Similarly, the words "dikirim", "kirimkan" and "dikirim", after going through the stem cutting process, become the root word "boleh". The root causes the words in the review to take their basic form and become the same term. The password removal process is then carried out to remove the password from consideration. reviews and in online buying and selling. An example of a list of stop words used is shown in the table below.

Table 9. List of Stopwords

No	Stopword	Number of Reviews
1	Very	68
2	Good	52
3	Which	97
4	Untuk	89
5	For	44
6	So	55
7	In	77
8	Appropriate	86
9	Economical	17
10	But	21

As seen in the table above, the word "yang" is included in the list of most frequently occurring stopwords, appearing 97 times, and the word "untuk" 89 times. In addition to words, numbers are also included in stopwords. These numbers have no effect on sentiment analysis and can be removed to reduce noise and increase effectiveness. Overall pre-processing results.

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3.5 Support Vector Machine

This study obtained data from a dataset obtained using the Support Vector Machine method, divided into 200 training data sets and 50 test data sets. The following image shows the script used to crawl the data using the Google Colab programming language.

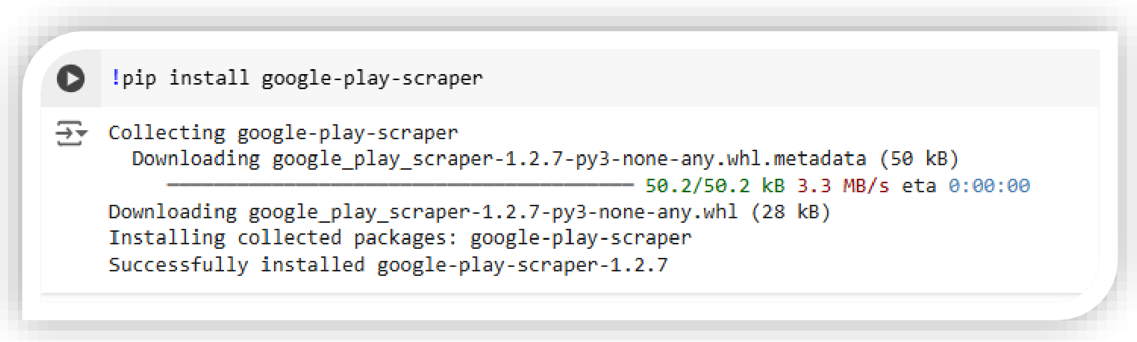

Figure 2. SVM Google Colab

The Replace operator removes symbols, URLs, and usernames. The Trim operator removes spaces at the beginning of a sentence. The Filter Examples operator filters out invalid entries, such as blank or missing values. The Remove Duplicates operator removes duplicate rows in a dataset, ensuring that each row appears only once. After the dataset cleaning process is complete, the next step is the labeling stage, which is the process of providing or marking text or data with labels or classifications that aim to indicate the opinions or feelings contained therein.

At this stage, the text is changed from capital letters to lower case entirely (lower case) using the Transform Cases operator in the system by distinguishing negative, positive and neutral sentiments.

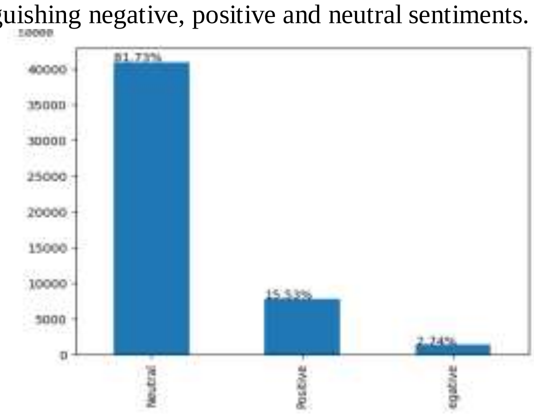

Figure 3. Process in Graphic Form

3.6 Evaluation

In the evaluation phase, a performance operator is used to generate a confusion matrix, which is applied to the test data. This data is then processed by the previously created Support Vector Machine algorithm model to test the algorithm's performance.

Table 10. Confusion Matrix

	Negatif	Positif
Pred. Negatif	TN	FN
Pred. Positif	FP	TP

In the table above, the Confusion Matrix has four main sections: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). The manual calculation formula is used to determine the difference between the values calculated using Rapidminer and the manual calculation.

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$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}\ x\ 100\ \%$$

$$Precision = \frac{TP}{TP + FP}\ x\ 100\ \%$$

$$Recall = \frac{TP}{TP + FN}\ x\ 100\ \%$$

Based on the results of research conducted using the RapidMiner tool with the SVM algorithm, the accuracy results for the confusion matrix were 80.31%.

	true negatif	tru positif	class precision
pred. Negatif	546	41	95. 35%
pred. Positif	273	810	74.20%
class. recall	65.04%	98.50%	

The table above shows 546 True Negatives (TN), indicating the number of truly negative reviews correctly predicted as negative by the model. Meanwhile, True Positives (TP) reached 810, representing the number of positive reviews correctly predicted. However, 41 False Negatives (FN) were found, which are positive reviews but incorrectly predicted as negative, and 273 False Positives (FP) that should have been negative but were incorrectly predicted as positive. The precision of negative reviews of 95.35% indicates the accuracy in classifying negative reviews, and the precision of positive reviews of 74.20% indicates how accurately the model classifies reviews as positive. Meanwhile, the Recall for negative reviews of 65.04% and the detection rate for positive reviews of 98.50% indicate how well the model is in identifying positive or negative reviews. In this study, an error rate of 20.67% was found. The process of calculating the performance confusion matrix value in the Support Vector Machine (SVM) method can be done manually using the following formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}\ x\ 100\ \%$$

$$Accuracy = \frac{810 + 546}{810 + 546 + 273 + 41}\ x\ 100\ \%$$

$$Accuracy = \frac{1356}{1670}\ x\ 100\ \% = 81.19\%$$

From the calculation results above, it shows that the accuracy level is 81.19% from the classification test carried out using the Support Vector Machine (SVM) algorithm.

$$Recall = \frac{TP}{TP + FN}\ x\ 100\ \%$$

$$Recall = \frac{810}{810 + 41}\ x\ 100\ \%$$

$$Recall = \frac{810}{851}\ x\ 100\ \% = 95.18\%$$

From the calculation results above, the recall value of 95.18% shows how well the model is in identifying reviews from the classification test carried out using the Support Vector Machine (SVM) algorithm.

$$Precision = \frac{TP}{TP + FN}\ x\ 100\ \%$$

$$Precision = \frac{810}{810 + 273}\ x\ 100\ \%$$

$$Precision = \frac{810}{851}\ x\ 100\ \% = 74.79\%$$

From the calculation results above, the precision value of 74.78% shows the accuracy of the model in classifying reviews.

In the negative sentiment image, the keyword that frequently appears is "driver." This is because many customers complain that drivers take a long time to deliver food because they take double orders or more than one order. Furthermore, customers also complain that drivers don't understand the delivery location, resulting in frequent wrong

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addresses. The keyword "expensive" also frequently appears in negative sentiment, due to high shipping costs and parking fees charged to customers. Recommendations based on the characteristics of negative sentiment include improving service quality, disabling the double order feature, and evaluating the accuracy of the delivery location.

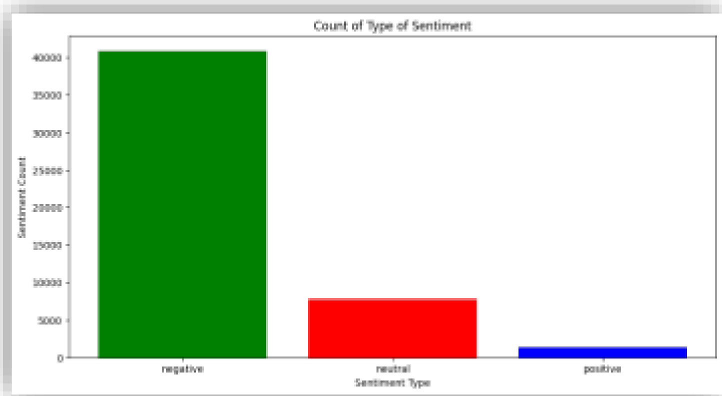

Figure 4. Count of Type of Sentiment

4. CONCLUSION

This study analyzes e-commerce user reviews of the sales system using the NPL and SVM algorithms. The results of the analysis show that the e-commerce user review data for the online sales system divides into two groups: those who received positive reviews and those who received negative reviews. In addition, by using the NPL and SVM algorithms, researchers can gain a better understanding of e-commerce user reviews of the online sales system, because we can identify distribution elements and provide an estimate of the probability of satisfaction for each e-commerce user. Based on the results of this analysis, it can be concluded that there are significant differences in satisfaction with the online sales system, steps that must be taken to improve satisfaction. This study successfully demonstrated the effectiveness of Natural Language Processing (NLP) techniques combined with Support Vector Machine (SVM) algorithms in classifying user sentiments from e-commerce reviews. The preprocessing steps, including tokenization, stop-word removal, and TF-IDF vectorization, significantly enhanced the quality of the input data and enabled the SVM model to achieve a high classification accuracy. Results indicate that the SVM model performs robustly in distinguishing between positive, negative, and neutral sentiments, making it a reliable tool for automated sentiment analysis in the e-commerce domain. These findings suggest that implementing such a system can support businesses in better understanding customer feedback, improving service quality, and informing strategic decision-making. Future work may involve exploring deep learning models, multilingual data, and real-time sentiment tracking for broader applicability and higher accuracy.

REFERENCES

[1] Alwendi, "Penerapan E-Commerce Dalam Meningkatkan," *Manaj. Bisnis*, vol. 17, no. 3, pp. 317–325, 2020, [Online]. Available: http://journal.undiknas.ac.id/index.php/magister-manajemen/

[2] Y. L. . Rehatalanit, "Peran E-Commerce Dalam Pengembangan Bisnis," *J. Teknol. Ind.*, vol. 5, no. 0, pp. 62–69, 2021, [Online]. Available: https://journal.universitassuryadarma.ac.id/index.php/jti/article/view/764

[3] Selsa Dharma Wulan, "Manfaat dan Tantangan E-Commerce Dalam Ekonomi Digital di Bidang Bisnis," *Pros. Semin. Nas. Ilmu Manaj. Kewirausahaan dan Bisnis*, vol. 1, no. 1, pp. 42–50, 2024, doi: 10.61132/prosemnasimkb.v1i1.5.

[4] D. E. B. Jabat, L. L. Tarigan, M. Purba, and M. Purba, "Pemanfaatan Platform E-Commerce Melalui Marketplace," *SKYLANDSEA Prof. J. Ekon. Bisnis dan Teknol.*, vol. 2, no. 2, pp. 16–21, 2022, [Online]. Available: https://jurnal.yappsu.org/index.php/skylandsea/article/view/85

[5] S. K. Kim and M. Park, "Effectiveness of person-centered care on people with dementia: A systematic review and meta-analysis," *Clin. Interv. Aging*, vol. 12, pp. 381–397, 2017, doi: 10.2147/CIA.S117637.

[6] D. F. Anisa and A. E. Yulianto, "Pengaruh Brand Image, Promotion, Dan Online Customer Review Terhadap Keputusan Pembelian Produk Mie Gacoan Cabang Manyar Di Platform Shopeefood," *J. Ilmu dan Ris. Manaj.*, vol. 13, no. 2, pp. 1–16, 2024.

[7] H. Kurniawan, M. A. Miftakhurahmat, and U. Enri, "Analisis Sentimen pada Ekspedisi Kurir Online di Indonesia Menggunakan Algoritma Naive Bayes," *VISA J. Vis. Ideas*, vol. 4, no. 3, pp. 1002–1012, 2024, doi: 10.47467/visa.v4i3.5140.

[8] Z. Sitorus, A. Marsya, D. Ramatika, and R. S. Siburian, “Analysis of Online Shopping Addiction Level Using the K-nearest Neighbor Algorithm at SMK Negeri 1 Tanjung Pura,” *J. Inf. Technol. Comput. Sci. Electr. Eng.*, vol. 1, no. 2, pp. 134–138, 2024, doi: 10.61306/jitcse.v1i2.

[9] M. Angawi and Z. Tasir, “Blended Learning Research: A Systematic Review and Identification of Future Research Gaps,” *Int. J. Acad. Res. Progress. Educ. Dev.*, vol. 13, no. 3, pp. 2993–3017, 2024, doi: 10.6007/ijarped/v13-i3/22216.

[10] Z. A. W. Sugandi and S. Sarmini, “Implementasi Metode Support Vector Machine (SVM) Pada Sistem Rekomendasi Produk Perawatan Wajah Berbasis Web,” *J. Sist. dan Teknol. Inf.*, vol. 12, no. 3, p. 388, 2024, doi: 10.26418/justin.v12i3.74905.

[11] N. Mardiah, L. Marlina, K. Khairul, Z. Sitorus, and M. Iqbal, “Analysis Of Indonesian People’s Sentiment Towards 2024 Presidential Candidates On Social Media Using Naïve Bayes Classifier and Support Vector Machine,” *Build. Informatics, Technol. Sci.*, vol. 6, no. 2, pp. 950–960, 2024, doi: 10.47065/bits.v6i2.5766.

[12] Z. Sitorus, M. Saputra, S. N. Sofyan, and Susilawati, “Sentiment Analysis of Indonesian Community Towards Electric Motorcycles on Twitter Using Orange Data Mining,” *INFOTECH J.*, vol. 10, no. 1, pp. 108–113, 2024, doi: 10.31949/infotech.v10i1.9374.

[13] M. Baha’uddin and Z. Fatah, “Penerapan Data Mining Clustering K-Means Dalam Mengelompokkan Data Penduduk Penyandang Disabilitas,” *Gudang J. Multidisiplin Ilmu*, vol. 2, no. 10, pp. 86–94, 2024, [Online]. Available: https://gudangjurnal.com/index.php/gjmi

[14] A. Wahyu Istalama Firdaus, “Text Mining Dan Pola Algoritma Dalam Penyelesaian Masalah Informasi : (Sebuah Ulasan),” *J. JUPITER*, vol. 13, no. 1, p. 66, 2021.

[15] K. Z. Mahmoud, B. S. Obeidat, and M. A. Ishmais, “Roasted sesame hulls improve broiler performance without affecting carcass characteristics,” *Ital. J. Anim. Sci.*, vol. 14, no. 3, pp. 495–501, 2015, doi: 10.4081/ijas.2015.3957.

[16] H. Abijono, P. Santoso, and N. L. Anggreini, “Algoritma Supervised Learning Dan Unsupervised Learning Dalam Pengolahan Data,” *J. Teknol. Terap. G-Tech*, vol. 4, no. 2, pp. 315–318, 2021, doi: 10.33379/gtech.v4i2.635.

[17] A. Rifa’i, H. Sujaini, and D. Prawira, “Sentiment Analysis Objek Wisata Kalimantan Barat Pada Google Maps Menggunakan Metode Naive Bayes,” *J. Edukasi dan Penelit. Inform.*, vol. 7, no. 3, p. 400, 2021, doi: 10.26418/jp.v7i3.48132.

[18] M. K. Anam, T. A. Fitri, A. Agustin, L. Lusiana, M. B. Firdaus, and A. T. Nurhuda, “Sentiment Analysis for Online Learning using The Lexicon-Based Method and The Support Vector Machine Algorithm,” *Ilk. J. Ilm.*, vol. 15, no. 2, pp. 290–302, 2023, doi: 10.33096/ilkom.v15i2.1590.290-302.

[19] D. Hidayat and R. Heryatno, “Kajian Pustaka Penelitian Perilaku Pengguna e-Wallet di Indonesia,” *Manaj. Bus. Innov. Conf.*, vol. 7, no. Upadhayaya 2012, pp. 80–89, 2024, [Online]. Available: https://jurnal.untan.ac.id/index.php/MBIC/index