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Comparative Sentiment Analysis of Delivery Service PT.POS Indonesia and J&T Express on Twitter Social Media Using The Support Verctor Machine Algorithm

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Abstract

Based on a survey conducted by the Top Brand Award in the courier service category, the J&T Express company is in the highest position from 2018 to 2021 beating Pos Indonesia. Social media Twitter is a place that is often used by customers to submit complaints and opinions regarding the services of a company. The method used to determine the tendency of opinions to contain positive or negative sentiments is sentiment analysis. Sentiment analysis will classify the polarity of the text in sentences or documents to find out whether the opinions Expressed are positive or negative. This study uses the Support Vector Machine (SVM) algorithm. The results of the user tweet data used are as many as 1000 data with details of data 206 (20.6%) have positive sentiments and 794 (79.4%) have negative sentiments. In the Pos Indonesia tweet data, 110 positive sentiment data were obtained, while the positive sentiment data in the J&T Express tweet data was 96 data. This shows that the Pos Indonesia delivery service has better customer service than J&T Express. The highest level of accuracy using the SVM algorithm in classifying sentiment is 80.14% with a comparison of 70% training data and 30% test data with an average precision of 90%, an average recall of 51.74% and an average f-measure 47.80%.

Keywords: *J&T Express, Pos Indonesia, Sentiment, Support Vector Machine, Twitter*

1. Introduction

The development of science and technology, the flow of information exchange is also becoming faster at this time. The need for information sources is increasing and information is considered as something very important, especially for business people. Obtaining the right and fast information will help in the progress of an organization to be able to make changes and answer the problems it faces [1].

Utilizing technological developments, one of which is the internet, currently many business people are marketing their products through e-commerce platforms so they can make buying and selling transactions online. Developments that occur in the use of e-commerce also make a significant increase in the use of delivery services. The need for delivery services continues to increase because sellers need delivery services to deliver ordered products to buyers both in Indonesia and abroad [2].

Delivery service providers in Indonesia include PT Pos Indonesia and PT Global Jet Express (J&T Express). PT Pos Indonesia is a State-Owned Enterprise engaged in delivery services with delivery services throughout Indonesia and abroad. Meanwhile, PT Global Jet Express or better known as J&T Express is a private company that is also engaged in delivery services. The J&T Express shipping service was founded in Indonesia in 2015 which is still relatively new when compared to Pos Indonesia which has been established since 1746. Even though it is a newcomer, J&T Express has proven to be able to compete with large companies in the same field. Based on a survey conducted by the Top Brand Award in the courier service category, the J&T Express company is in the highest position from 2018 to 2021 beating Pos Indonesia.

The increase in the number of Pos Indonesia and J&T Express users is of course the more opinions submitted by users regarding these delivery services. Social media Twitter is a place that is often used by customers to submit complaints and opinions regarding the services of a company [3]. Even though many are helped by the delivery service, not all opinions contain positive sentiment. Some users may also provide opinions that contain negative sentiments. The more complaints or negative sentiments that customers give, the more attention is needed for every company that receives complaints or negative comments to improve products or services [4]. To find out the tendency of these opinions to contain positive or negative sentiments, a method is needed to analyze the opinions that users give about services from Pos Indonesia and J&T Express.

The method that can be used to determine the tendency of opinions to contain positive or negative sentiments is sentiment analysis. Sentiment analysis will classify the polarity of the text in a sentence or document to find out whether the opinion expressed in the sentence or document is positive or negative [5]. There are several algorithms that can be used to perform sentiment analysis including Support Vector Machine (SVM), Naïve Bayes Classifier, k-Nearest Neighbor (KNN), Artificial Neural Network (ANN) and Decision Tree.

Based on the search results, there are several studies using different classification algorithms in their research with the aim of comparing performance between algorithms. One of them is research entitled "Comparison of Accuracy and Processing Time of K-NN and SVM Algorithms in Twitter Sentiment Analysis". This study aims to compare the level of accuracy and processing time of the K-NN and SVM algorithms in classifying tweet data from social media Twitter. The results of this study show that the SVM algorithm is superior in terms of accuracy with a value of 89.70%, while the KNN algorithm is superior in processing time with a time of 0.0160 seconds [6]. Then research was conducted by with the title "Analysis of Sentiment of Ruang Guru Applications on Twitter Using Classification Algorithms". This study aims to compare the Naïve Bayes, KNN and SVM classification algorithms that use feature selection and those that do not use feature selection and compare the Area Under Curve (AUC) values of each algorithm to find out the most optimal algorithm. The results of this study found that the SVM algorithm was the most optimal with the highest accuracy value of 78.55 and an AUC of 0.853 [7]. Based on these studies, this research will use the Support Vector Machine (SVM) algorithm because it is felt to have a better level of accuracy than other algorithms. The Support Vector Machine (SVM) algorithm is also used because it can be applied to entity tweets with a better level of accuracy than other classification algorithms.

Based on the background that has been described, this study aims to carry out sentiment analysis on the opinions of users of Pos Indonesia and J&T Express delivery services on Twitter social media and measure the performance of the Support Vector Machine (SVM) Algorithm in classifying data.

2. Research Methodology

The following stages of the method carried out in this study as shown in Figure 1.

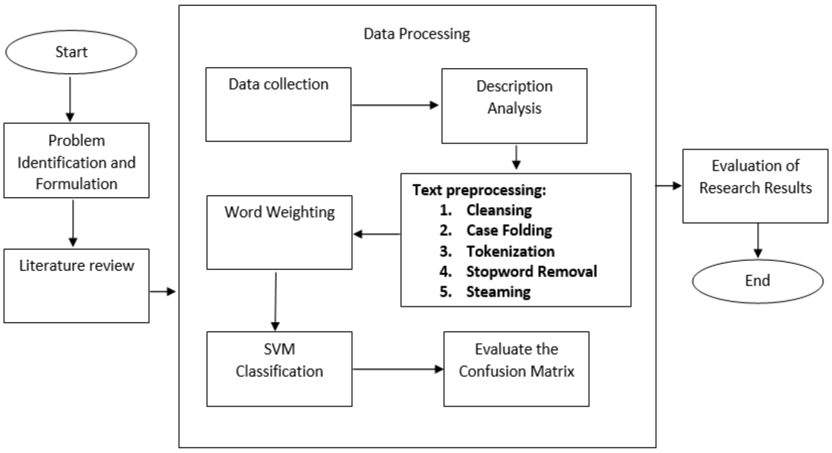

Figure 1. Research Methodology

1. Identification and formulation of the problem

At this stage, identification of the problem is carried out by looking at the current conditions and situation. The identification results obtained information that users of delivery services are increasing, especially during pandemic conditions. This is due to an increase in the number of online buying and selling transactions that require delivery services. The increase in the number of users was also accompanied by an increase in the number of sentiments from users regarding the shipping services used.

2. Library Studies

At this stage, a literature study related to the topic of sentiment analysis was carried out in order to find out the appropriate method for this research. There are several topics used in the literature study, such as text mining, text preprocessing, word weighting, classification, Support Vector Machine (SVM), confusion matrix and k-fold cross validation.

3. Sentiment analysis process

At the data processing stage, it is carried out through several processes. Data collection, descriptive analysis, text preprocessing, word weighting, support vector machine (SVM) classification, evaluation.

4. Evaluation of Research Results

At the evaluation stage, measurement and review of research results are carried out. Measurement and review aims to compare the objectives of the research with the level of success achieved. The evaluation phase will produce information that can be used to draw research conclusions.

3. Result And Discussion

3.1. Sentiment Analysis of Tweet Data for J&T Express and Pos Indonesia Services

In this research, data was collected in the form of tweets from Pos Indonesia and J&T Express users on Twitter social media. Data collection was carried out by crawling technique using Rapidminer Studio software version 9.10 connected to Twitter social media via a Twitter API connection. The data obtained from the crawling process is then saved in the Microsoft Excel Worksheet (.xlsx) format. This study uses data with a total of 1000 tweets. The data consists of the latest 500 tweet data containing sentiment towards J&T Express and the latest 500 tweet data containing sentiment towards Pos Indonesia.

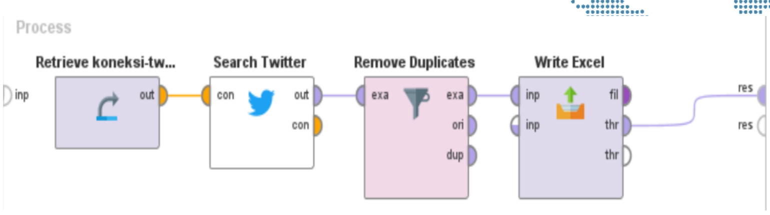

Figure 2. Twitter Data Crawling Process

Figure 2 shows the process of crawling or retrieving data from social media Twitter using several operators in RapidMiner Studio. The retrieve operator serves as a link to Twitter. The retrieve operator contains the connection file between RapidMiner and the Twitter API that has been created. The Twitter search operator functions to enter search keywords that will be used to search for tweet data. The search keywords used in this study were j&t, jnt, pos Indonesia and posindonesia. To eliminate or anticipate the existence of the same tweet data, the remove duplicate operator is used to delete similar data. The write to excel operator is used to save search result data into a file in Microsoft Excel Worksheet (.xlsx) format. The next step is to do text preprocessing, in text preprocessing this is the initial process of processing the dataset before it can be processed for classification with the Support Vector Machine (SVM) algorithm. There are several stages of text preprocessing carried out in this study, namely:

a) Cleansing

At the cleansing stage, data is cleaned from various characters or symbols that have no meaning and do not affect sentiment in the data. The stages of the cleansing process are shown in Figure 4.

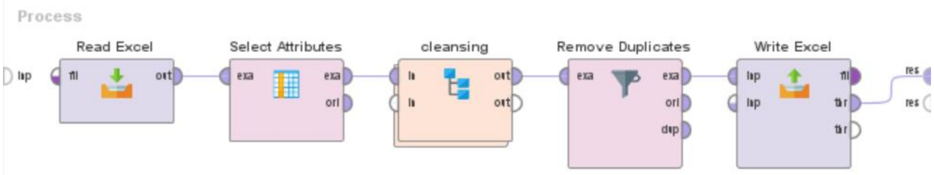

Figure 3. Twitter Data Cleansing Process

Figure 3 shows the stages of the first cleansing process used by the read excel operator to read the tweet data obtained earlier. The select attributes operator functions to separate tweet data in the text column from other unnecessary data. The text column is used because it contains tweets from delivery service users containing sentiments. After the data is only in the form of tweets, then the data is cleaned in the subprocess cleaning operator which contains several other processes. The data that has been processed is then checked again using the remove duplicate operator and saved again using the write to excel operator as shown in Figure 4.

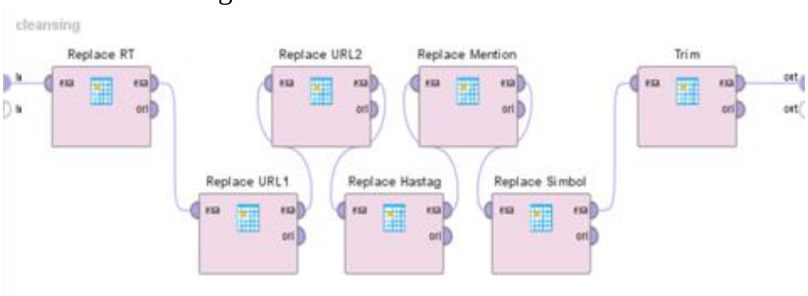

Figure 4. Cleansing Sub-Process

Figure 4 shows the operator subprocess cleansing, there are several processes for cleaning data as shown in Figure 5. The replace operator is used to remove RT words, URLs, hashtags (#), mentions, various symbols and numbers. There are two replace URLs because the process for deleting URLs in the middle and at the end of the tweet is different. The trim operator is used to remove unnecessary spaces from data.

b) Case Folding

In the case folding stage, the process of changing capital letters in the text of the tweet data is carried out in all lowercase letters. This stage is carried out for the uniformity of irregular text in the use of letters in writing tweets, so that the tweets are written inconsistently. To carry out the case folding stage, one of the operators from RapidMiner Studio is used, namely the transform case operator. In table 1 are some examples of the process of uniforming the form of letters where all letters in the text are converted to lower case.

Table 1. Stages Of Case Folding And Data Labeling

Tweet	**Label**
pak tolong di bantu follow up paket belum sampai no barcode ini pelanggan sy komplain di pos tujuan semarang paket nya kok malah nyasar ke banjarmasin	Negative
lohh itu tujuan semarang bos gmn sih kok malah nyasar ke banjarmasin	Negative
sy malah kena komplain ini sama pelanggan sy gara kelalaian petugas anda bentuk tanggung jawab nya mana	Negative
saya ada paket dr china pajak sudah sy bayar via virtual account tapi pas barangnya dikirim saya ditagih lagi kenapa begitu ya pas saya lagi ga di tempat jadi temen saya yang bayar ditagih rb sama pak posnya padahal saya sudah bayar pakai virtual account	Negative
kirim ke luar negeri jangkauan lebih luas kantor pos giro sumedang	Positive

In the case folding stage, letter uniformity is carried out where the capital letters will be changed to lower case, for example like the letters in the word "REACH" where the word as a whole has capital letters, then with the case folding stage the word is changed to "reach". Another example occurs in the word "Barcode" where the word has a capital letter at the beginning of the word which is then changed to "barcode" and so on.

c) Tokenization

The tokenization stage is the stage which separates words, symbols, phrases, and other important entities from a text. The tokenization stage is carried out using the tokenize operator in RapidMiner Studio. The results of the implementation of the tokenization stage are shown in table 2.

Table 2. Tokenization Stages

t1	Pak	Tolong	Di	bantu	follow	up
	Paket	belum	Sampai	no	barcode	ini
	Pelanggan	sy	Complain	di	pos	tujuan
	Semarang	paket	Nya	kok	malah	nyasar
	Ke	banjarmasin				
t2	Lohh	itu	tujuan	semarang	bos	gmn
	Sih	kok	malah	nyasar	ke	banjarmasin
t3	Sy	malah	kena	komplain	ini	sama
	Pelanggan	sy	gara	kelalaian	petugas	anda
	Bentuk	tanggung	jawab	nya	mana	
t4	Saya	ada	paket	dr	china	pajak
	Sudah	sy	bayar	via	virtual	account
	Tapi	pas	barangny a	dikirim	saya	ditagih
	Lagi	kenapa	begitu	ya	pas	saya
	Lagi	ga	di	tempat	jadi	temen

	Saya	yang	bayar	ditagih	rb	sama
	Pak	posnya	padahal	saya	sudah	bayar
	Pakai	virtual	account			
t5	Kirim	ke	luar	negeri		

Table 2 displays the results of the tokenization stage where word separation is carried out in sentences. In RapidMiner Studio, the tokenization stage uses the process document operator. The data in table 3 is an example of a term from an initial amount of 1000 data and only 5 terms are entered.

d) Stopword Removal

This stage aims to reduce the words in the corpus using stopwords. Stopwords consist of words which if omitted do not reduce the information contained in the sentence. Words included in stopwords usually consist of personal pronouns (I, you, you), conjunctions (or, and, then), interrogative words (what, where, how) and other words that have no significant meaning in determining document discussion. At this stage, stopword filter operators (dictionary) are used in RapidMiner Studio and Stopword Tala Indonesian as a dictionary. The Indonesian Tala Stopword as a dictionary is shown in Figure 5.

ada
adalah
adanya
adapun
agak
agaknya
agar
akan
akankah
akhir
akhiri
akhirnya

Figure 5. Stopword Dictionary

This stage uses the operator on RapidMiner, namely Stopword. Tweets collected for research are in the Indonesian language, so the Stopword operator is selected in the text processing stage so that you can choose a dictionary according to the language used. The Indonesian dictionary has been made manually in .txt format, then the dictionary is inputted into the stopword operator so that the word classification that occurs produces Indonesian. The format of the dictionary used is as shown in Figure 5. This stage aims to produce only words or terms that have meaning according to the language dictionary entered in the Stopword process.

e) Filter by Length

The next stage is the filter by length stage which aims to remove conjunctions and abbreviations that do not affect the sentiment contained in the data. At this stage, the filter tokens operator is used which is set not to display words with a number of letters less than or equal to 4. The results of the implementation of the Filter by Length stage are shown in table 3.

Table 3. Filter Stages By Length

t1		tolong		bantu		
	Paket				barcode	
	Pelanggan		komplain		pos	
		paket				

t2						
				nyasar		
t3				komplain		
	Pelanggan			kelalaian	petugas	anda
t4			paket			pajak
			bayar			
			barangnya	dikirim		ditagih
				tempat		temen
			bayar	ditagih		
		posnya				bayar
	Pakai					
t5	Kirim		luar			

f) Stemming

This stage is a continuation of the previous stage, the words resulting from the classification from the stopword removal stage are then processed at this stage to become standard words, such as the word "address" becomes "address", "help" becomes "help" and so on. The words that were successfully classified were 90 words or terms (t) out of 1000 data. The results of the stemming stages are shown in table 4.

Table 4. Stemming Stages

t1	tolong	bantu	paket	barcode	pelanggan	komplain
	pos	paket	nyasar			
t2	nyasar					
t3	komplain	pelanggan	lalai	petugas	anda	
t4	paket	pajak	bayar	barang	kirim	tagih
	tempat	temen	bayar	tagih	pos	bayar
	pakai					
t5	kirim	luar				

3.2. Overview of Users of the Indonesian Postal Service and J&T Express

Sentiment analysis to obtain public opinions taken from social media Twitter using several data processing operators available in Rapidminer 9.10. The sentiment obtained is divided into 2 (two) classes, namely positive sentiment and negative sentiment. The details of the data obtained are shown in table 5.

Table 5. Results Of Cleaning Data Twitter Pos Indonesia And J&T Express

Delivery Services	Total Positive Sentiment	Total Negative Sentiment	Amount
Pos Indonesia	110	390	500
J&T *Express*	96	404	500
Amount of data	206	794	1000

Based on the data in table 5, it can be concluded that public opinions expressed or conveyed via social media Twitter tend to be negative. This conclusion is due to the amount of data with negative sentiment, which is 794 data, which is more than the data with positive sentiment, which is 206 data.

Fill in the comments that contain negative sentiments, ranging from service, time to receive packages to human resources that are criticized by customers when using J&T Express and Pos Indonesia delivery services.

3.3. Word Weighting (TF-IDF)

In the word weighting process using the TF-IDF algorithm, the first step is to determine the term (t) to be used in processing sentences or text comments that were collected previously at the data preprocessing stage. Next, an analysis process is carried out on which documents contain the term (t) that has been determined. If it contains term (t), then the value entered is 1 and if not, it is given a value of 0. Likewise, if a sentence/document contains more than one term (t), then it is written according to the number of terms (t) used in the document. The process is carried out to find the value of TF (Term Frequency).

Then for the next step, namely calculating the IDF, the following formula is used:

$$IDF = log\frac{D}{df} \tag{1}$$

After all term (t) is calculated using the formula above. So the next step is to calculate the TF-IDF. The steps for calculating TF-IDF are carried out by multiplying the number of IDF with documents containing terms (t) marked with the numbers 0 and 1 or more. Then after it has been entered, the values are aligned as when calculating TF. The details of the data obtained are shown in table 6.

Table 6. Weighting Of Tf-Idf Words

Term	Admin	End	Active	n	Website
D1	0	0	0	...	0
D2	0	0	0	...	0
D3	0	0	0	...	0
D4	0	0	0	...	0
D5	0	0	0	...	0
Dn	...	...	...		
D1000	0	0	0	...	0
DF	15	1	6	...	6
IDF	1,82	3	2,22	...	2,22

3.4. Classification of Support Vector Machines

The data obtained from tweets via Twitter social media containing comments from Pos Indonesia and J&T Express which were successfully obtained and processed were 1,000 data and divided into 2 sentiment classes, namely positive sentiment and negative sentiment. The data that has passed the preprocessing stage is divided into 2, namely training data and testing data using the crossvalidation method. This test was carried out 7 times with different amounts of training data and test data. Test data and training data that have been divided in each experiment will be classified using SVM with a kernel polynominal function. The Rapidminer series in classifying training data and test data that has been divided in the above comparison will be shown in Figure 6.

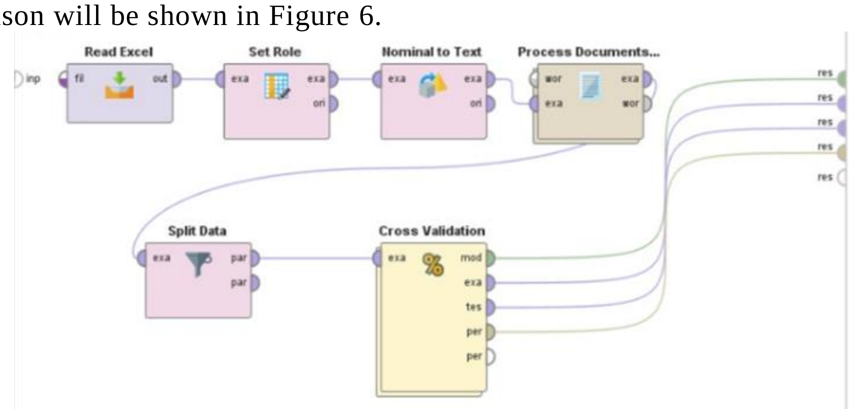

Figure 6. SVM Classification In Rapidminer

The SVM algorithm process is in operator cross validation, the circuit is as shown in Figure 7.

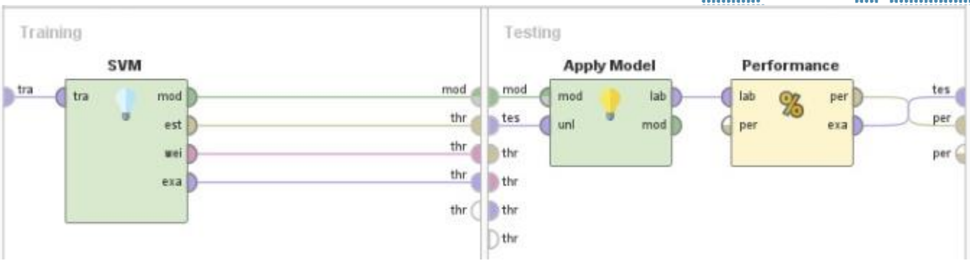

Figure 7. SVM Algorithm Process

Table 7 is the result of the learning model classified with seven trials where each test obtains a matrix as a representative of the actual class and the predicted class. After obtaining the model results from learning with SVM, testing is carried out with the test data that has been divided.

Table 7. Comparison Of Test Data And Training Data

Data Comparison		Amount of data	
Train Data	**Test Data**	**Train Data**	**Test Data**
80%	20%	800	200
70%	30%	700	300
60%	40%	600	400
50%	50%	500	500
40%	60%	400	600
30%	70%	300	700
20%	80%	200	800

Table 8 above shows the confusion matrix which is the predicted result using SVM which measures the performance of each class by calculating precision, recall and f-measure.

Table 8. Confusion Matrix

Actual Data	Predictive Data	
	Positive	**Negative**
Positive	The class of correctly predictable sentences is positive (TP)	Positive sentence class predicted negative (FP)
Negative	Negative sentence class predicted positive (FN)	Negative predictive sentence class is negative (TN)

Precision is used to calculate predicted class accuracy according to the actual class to produce accuracy. To measure precision, the following equation is used:

$$Precision = \frac{True\ Positif}{(True\ Positif + False\ Positif)} \quad (2)$$

The precision calculation for each sentence class uses the following equation:

$$\text{Positive} = \frac{TP}{(TP+FN)} \quad (3)$$

$$\text{Negative} = \frac{TN}{(TN+FP)} \quad (4)$$

Recall is used to measure the sensitivity of the measurement in the dataset or predictive ability of the system according to the level of truth for recalling relevant documents. Recall measurement uses the following equation:

$$Recall : \frac{True\ Positif}{(True\ Positif + False\ Positif)} \quad (5)$$

The recall calculation for each word class uses the following equation:

$$\text{Positive} = \frac{TP}{(TP+FP)} \quad (6)$$

$$\text{Negative} = \frac{TN}{(TN+FN)} \quad (7)$$

The F-measure calculation uses the following equation:

$$F - Measure = 2 \text{ x } \frac{Precision \text{ x } Recall}{Precision + Recall} \quad (8)$$

3.5. Experiment With Train And Test Data

In this study carried out several scenarios in conducting training and test data as follows:

a) The experiment with 20% training data and 80% test data is the first experiment, the results of which can be seen in Figure 8.

accuracy: 79.00% +/- 2.11% (micro average: 79.00%)

	true Negatif	true Positif	class precision
pred. Negatif	158	41	79.40%
pred. Positif	1	0	0.00%
class recall	99.37%	0.00%	

Figure 8. Training Data 20% And Test Data 80%

Figure 8 shows the results of the first experiment using a dataset that has been divided into 20% training data and 80% random test data which will be classified using SVM.

b) The experiment with 30% training data and 70% test data is the second experiment, the results of which can be seen in Figure 9.

accuracy: 79.33% +/- 1.41% (micro average: 79.33%)

	true Negatif	true Positif	class precision
pred. Negatif	238	62	79.33%
pred. Positif	0	0	0.00%
class recall	100.00%	0.00%	

Figure 9. Training Data 30% And Test Data 70%

Figure 9 uses a dataset that has been divided into 30% training data and 70% random test data which will be classified using SVM.

c) The experiment with 40% training data and 60% test data is the third experiment, the results of which can be seen in Figure 10.

accuracy: 79.25% +/- 1.21% (micro average: 79.25%)

	true Negatif	true Positif	class precision
pred. Negatif	317	82	79.45%
pred. Positif	1	0	0.00%
class recall	99.69%	0.00%	

Figure 10. Training Data 60% And Test Data 40%

Figure 10 uses a dataset that has been divided into 40% training data and 60% random test data which will be classified using SVM.

d) The experiment with 50% training data and 50% test data is the third experiment, the results of which can be seen in Figure 11.

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accuracy: 79.20% +/- 1.40% (micro average: 79.20%)

	true Negatif	true Positif	class precision
pred. Negatif	396	103	79.36%
pred. Positif	1	0	0.00%
class recall	99.75%	0.00%	

Figure 11. Training Data 50% And Test Data 50%

Figure 11 uses a dataset that has been divided into 50% training data and 50% random test data which will be classified using SVM.

e) The experiment with 60% training data and 40% test data is the third experiment, the results of which can be seen in Figure 12.

accuracy: 79.67% +/- 1.05% (micro average: 79.67%)

	true Negatif	true Positif	class precision
pred. Negatif	474	120	79.80%
pred. Positif	2	4	66.67%
class recall	99.58%	3.23%	

Figure 12. Training Data 60% And Test Data 40%

Figure 12 uses a dataset that has been divided into 60% training data and 40% random test data which will be classified using SVM.

f) The experiment with 70% training data and 30% test data is the third experiment, the results of which can be seen in Figure 13.

accuracy: 80.14% +/- 1.25% (micro average: 80.14%)

	true Negatif	true Positif	class precision
pred. Negatif	556	139	80.00%
pred. Positif	0	5	100.00%
class recall	100.00%	3.47%	

Figure 13. Training Data 70% And Test Data 30%

Figure 13 uses a dataset that has been divided into 70% training data and 30% random test data which will be classified using SVM.

g) The experiment with 80% training data and 20% test data is the third experiment, the results of which can be seen in Figure 14.

accuracy: 79.87% +/- 1.24% (micro average: 79.88%)

	true Negatif	true Positif	class precision
pred. Negatif	634	160	79.85%
pred. Positif	1	5	83.33%
class recall	99.84%	3.03%	

Figure 14. Training Data 80% And Test Data 20%

Figure 14 uses a dataset that has been divided into 80% training data and 20% random test data which will be classified using SVM.

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Recapitulation of the experimental results of training data and test data The recapitulation of all the training and test data sharing experiments is shown in table 9.

Table 9. Recapitulation Of 7 Trials

Train/Test Data	Positive			Negative			Accuracy
	Precision	Recall	F-Measure	Precision	Recall	F-Measure	
20%/80%	0	0	0	79,4	99,37	88,27	79
30%/70%	0	0	0	79,33	100	88,47	79,33
40%/60%	0	0	0	79,45	99,69	88,43	79,25
50%/50%	0	0	0	79,36	99,75	88,39	79,20
60%/40%	66,67	3,23	6,16	79,8	99,58	88,60	79,67
70%/30%	100	3,47	6,71	80	100	88,89	80,14
80%/20%	83,33	3,03	5,85	79,85	99,84	88,73	79,87

Table 9 shows that the highest accuracy rate is 80.14% with a data comparison of 70% training data and 30% test data, while the lowest accuracy rate is 79% with a data comparison of 80% training data and 20% test data.

4. Conclusion

The results of the research that has been done can be concluded that there are several stages in conducting sentiment analysis, namely collecting data, conducting descriptive analysis, text preprocessing stages, word weighting, analysis with classification algorithms/models, and drawing conclusions. Each stage is interrelated so that no stage should be skipped to get the most relevant result. In the process of this research, 1000 user tweets were used, with details of 206 (20.6%) having positive sentiments and 794 (79.4%) having negative sentiments. In general, this shows that user sentiment towards Pos Indonesia and J&T Express delivery services tends to be negative. Negative sentiments varied, starting from the service, when the package was received, to the human resources that were criticized by the customer. In the Pos Indonesia tweet data, 110 positive sentiment data were obtained, while the positive sentiment data in the J&T Express tweet data was 96 data. This shows that the Pos Indonesia delivery service has better customer service than J&T Express. The highest level of accuracy using the SVM algorithm in classifying sentiment is 80.14% with a comparison of 70% training data and 30% test data with an average precision of 90%, an average recall of 51.74% and an average f-measure 47.80%.

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