Sentiment Analysis of Ojek Online User Satisfaction Based on the Net Brand Reputation Method

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***Abstract*—Gojek and Grab are the most popular and commonly used online motorcycle taxis today, based on a survey conducted by Hootsuite - We Are Social for January 2019 on the ranking of mobile applications by active monthly users of Indonesia, which shows Gojek and Grab and Ten. Not yet responded to how the response of the online motorcycle taxi users. Because the level of satisfaction of ojek users between Gojek and Grab is based on sentiment analysis from Twitter. Data withdrawal starts from September to December 2019 using twitterscraper with the keywords "@gojekindonesia or gojekindonesia" for Gojek and "@GrabID or GrabID" for Grab. The results of data retrieval are continued with the preprocessing stage to eliminate imperfect data. The result data from the preprocessing stage is divided into two parts, namely for drivers and companies, so we get 2933 tweets for Gojek drivers, 9979 tweets for Gojek companies, 2460 tweets for Grab drivers and 7923 tweets for Grab companies. This data will be used to measure the level of satisfaction using the Net Brand Reputation (NBR) method and the Naïve Bayes classification. The results showed that more tweets had negative meanings compared to positive meanings for Gojek and Grab.**

***Keywords*—Gojek, Grab, Naïve Bayes, Net Brand Reputation, Sentiment Analysis**

I. INTRODUCTION

The last few years in Indonesia have undergone a transformation, including in the field of transportation [1]. Transportation is a very important means in supporting human activities or mobility every day so it must be well prepared and safe because it is very influential in activities such as the economy, delivery of goods or services, passenger transportation and so on [2]. Various types of transportation in Indonesia, land transportation is one that is given special attention by the government and users of transportation services. Besides being cheap, up to now land transportation is still the belle of most Indonesian people [3].

Land transportation modes that are easily found and often used in daily life, one of which is motorcycle taxi. Ojeg in this paper is a mode of land transportation using a motorcycle that usually has a base (at the T-junction or in strategic places such as in front of the station or terminal) to wait for passengers [4]. Currently there are two types of motorcycle taxi services, namely "conventional motorcycle taxi" and "online motorcycle taxi" [5]. The shift from conventional transportation service users to online transportation is influenced by the sophistication of communication tools (technology) and the desire of people who always want convenience [4].

Some online motorcycle taxis found in Indonesia include Gojek, Grab, OK Jack, Indo-Jek, Bang Jek and others. Gojek and Grab are the most popular online motorcycle taxis and are often used today. This is based on a survey conducted by Hootsuite - We Are Social for January 2019 on the Ranking of Mobile Apps By Monthly Active Users in Indonesia, which shows that Gojek and Grab ranks eighth and tenth [6]. In addition to the survey, on the site www.play.google.com, Gojek has been downloaded more than 50 million, while Grab has been downloaded more than 100 million.

Each Ojek Online service provider has its own advantages that can make users feel satisfied with their service. In addition to excellence, service providers also need to pay attention from the aspects of shortcomings, so that users stay afloat and do not move to other service providers. Twitter is one type of social media that has 52% active users of all internet users in Indonesia based on a survey conducted by Hootsuite - We Are Social for January 2019 [6]. Twitter allows users to write a variety of topics and discuss problems that occur unlike some other social media that requires approval from both parties to connect with each other, Twitter allows users to track submissions (called tweets) from other users without getting approval. This is one reason why Twitter is a place for information flow and is used to determine the level of user satisfaction with the services provided.

How to find out the level of satisfaction of service users for services provided by service providers, both from companies or drivers, it is necessary to do sentiment analysis in which the data to be analyzed is taken from user tweets for each service provider. This Tweet will be categorized based on negative tweets and positive tweets to be used as a reference to determine the level of user satisfaction with service providers.

Tools use rapidminer to classify data that will produce accuracy, precison, recall and error rate values. This value will later be used as a reference as a comparison to find out the satisfaction level of online motorcycle taxi users based on service providers namely Gojek and Grab.

Then in this study will measure the level of satisfaction of online motorcycle taxi users between Gojek and Grab based on sentiment analysis from Twitter using the Net Brand Reputation method and the Naïve Bayes classification.

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II. Related Work

Sentiment analysis or opinion mining is a computational study of people's opinions, sentiments, and emotions through entities and attributes that are expressed in text form [7].Sentiment analysis is one part of data mining where the data can be classified based on positive or negative [8].

Research on sentiment analysis has been done before. kristiyanti et al's research stated that the Naïve Bayes algorithm is superior to the Support Vector Machine algorithm in classifying public opinion with Indonesian text on twitter for the prospective governor of the West Java Period 2018-2023 [9]. Parveen & Pandey in their research stated that the performance of the Naïve Bayes algorithm will increase when changing emoticons into meaningful words [10].

Vidya et al measured the level of satisfaction of mobile provider users in Indonesia based on reputation and classification. The method used to determine reputation is the Net Brand Reputation (NBR) while the method for classification is Support Vector Machine, Naïve Bayes, and Decision Tree [11].

The conclusion of the three studies [9], [10] and [11]. is that the calculation of net brend reputation (NBR) and naïve bayes is an algorithm that can be used to determine the level of satisfaction by adding emoticon conversions during preprocessing to improve naïve bayes performance.

III. Methodology

The tool used in this study uses Twitterscraper, Microsoft Excel and Rapidminer. Twitterscraper is a python library for retrieving data from Twitter. Microsoft Excel is used for preprocessing and calculating Net Brand Reputation (NBR), while Rapidminer is used in the Naïve Bayes classification. Figure 1 shows the stages of the study.

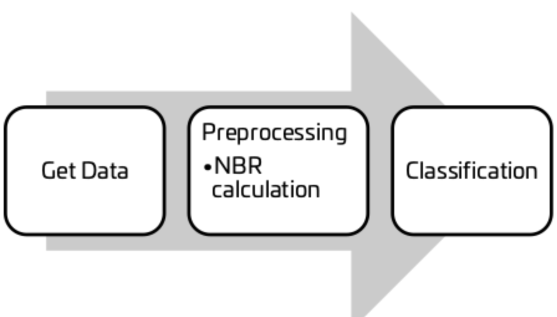

Fig. 1 Methodology

A. *Getting Data*

Data retrieval is done using twitterscraper [12]. The advantage of twitterscraper is that there is no need to use Twitter API for its use, making it easier to retrieve data, but the disadvantage of twitterscrapper is that the number of withdrawals depends on internet speed.

B. *Preprocessing*

Preprocessing is done to avoid imperfect data, interference with data, and inconsistent data [13]. Figure 2 shows the preprocessing stages.

1. Filtering, stage to sort the data drawn from the data based on the data needed only.
2. Remove Duplicates, the stage of deleting data that is considered to have the same tweet and retrieving one from the same tweet.
3. Converting Emoticons, change emoticons into meaningful words [10]. A list of converting emoticons is presented in table I.

TABLE I. Converting Emoticons

Emoticons				Converting
:d	:-d	:)	:-)	Smile
[illegible]	:-(	:[	:-[	Sad
x(	x-(	X(	X-(	Angry
:x	:-x	:X	:-X	Love
:-	:/	:-/		Confused
:,(	:"(	:'(		Crying
:D	:-D	=D	=-D	Laughing
B|	B-|	8|	8-|	Cool

4. Case Folding, homogenize letter shapes from large to small [14].
5. Remove Urls, stage of removing a url to reduce data that is not needed.
6. Tokenization, cutting input string based on the words that make it up [13].
7. Stemming, the stage of searching for root words by removing affixes to a word [15]. Stemming stages are carried out using sastrawi libraries [16].
8. Remove Stopwords, stopwords are words that do not have a specific meaning [14]. The remove stopwords stage is performed using the sastrawi library [16].
9. Manual Labeling, tweets will be labeled as positive and negative.

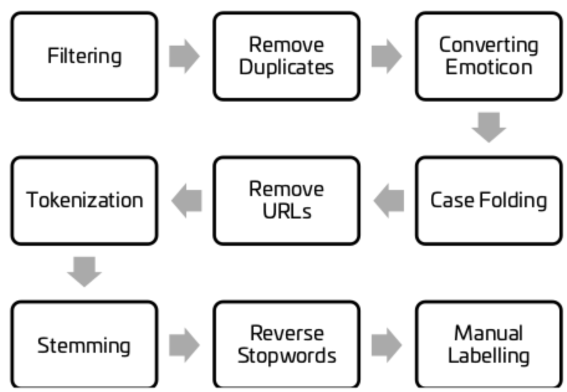

Fig. 2 Preprocessing Step

Data from the preprocessing stage is divided into two parts, namely for drivers and companies, so we get 2933 tweets for Gojek drivers, 9979 tweets for Gojek companies, 2460 tweets for Grab drivers and 7923 tweets for Grab companies.

C. *Classification*

The naïve Bayes classifier is based on the Bayes theorem discovered by Thomas Bayes in the 18th century [17]. the Naïve Bayes theorem can be seen in equation (1) [18].

$$P(H|X) = \frac{P(X|H).P(H)}{P(X)} \quad (1)$$

D. *Classification Evalulion*

Classification stages for drivers or companies Gojek and Grab will produce accuracy, precision, recall and error rate values. These values will be compared with each other to determine which classification is best based on each Gojek and Grab.

E. *Calculation of Net Brand Reputation (NBR)*

Net Brand Reputation (NBR) is the net reputation value of a brand digitally [11]. The purpose of the NBR is to simplify the measurement of consumer loyalty. The NBR formula can be seen in equation (2).

$$\left(\frac{Positive\ mentions - negative\ mentions}{Positive\ mentions + negative\ mentions}\right) x100\% \quad (2)$$

Net Brand Reputation (NBR) calculations are only based on the number of positive and negative tweets labeled from the Gojek and Grab datasets. The NBR value can be a number between -100 and 100, the higher the positive number, the NBR indicates that more tweets are considered positive.

IV. Result and Analysis

A. *Getting Data*

Data retrieval is done using twitterscraper with the keywords "@gojekindonesia or gojekindonesia" for Gojek and "@GrabID or GrabID" for Grab, starting from the beginning of September to the end of December 2019. The results of the data withdrawal are presented in table II.

TABLE II. Getting Data from Twitter

Data	Keywords	Values
Gojek	@gojekindonesia or gojekindonesia	125178 *tweet*
Grab	@GrabID or GrabID	130802 *tweet*

B. *Preprocessing*

The first stage to process the results of a withdrawal is filtering. The first stage of filtering is to look for tweets that have the word @gojekindonesia for Gojek and @GrabID for Grab, because not all tweets resulting from data retrieval have the word. The results of filtering obtained 56635 tweets for Gojek and 45648 tweets for Grab. The filtering stage is followed by searching and deleting tweets that have the words @jokowi and @prabowo, because tweets that have the word have meaning not to the user's response about the service provided. The results of this advanced filtering eliminated 451 tweets for Gojek and 115 tweets for Grab, so that 56184 tweets were obtained for Gojek and 45533 tweets for Grab.

The second stage is remove duplicates. The results of this stage eliminate 4555 tweets for Gojek and 5131 for Grab, so that it gets 51629 tweets for Gojek and 40402 tweets for Grab.

The third stage is converting emoticons, turning tweets that have emoticon symbols into words that have meaning, as described in table II.

The fourth stage is case folding, changing all tweets that have uppercase letters to lowercase letters.

The fifth stage is remove url, at this stage tweets that have url like http, https or pic.twitter.com are removed. Before the next stage, the remove duplicates stage is done again, this is because when the url is removed, there are several tweets that have the same data. The results of remove duplicates removes 575 tweets for Gojek and 387 tweets for Grab so that we get 51052 tweets for Gojek and 40015 tweets for Grab.

The sixth stage is tokenization, the characters in tweets like (?), (.), (/), (,), (!), (:), (-), (<), (>), () , ((), ([], (]), ('), ("), (=), (*), (%), (_), (;), (^), (#), (&), (\), (+), ($) and (|) are removed.

The seventh stage is stemming, at this stage removes the affixes to a word, such as the word "thwart" to the word "fail" and so forth.

The eighth stage is remove stopwods, at this stage it eliminates words that do not have certain meanings such as what, why, how and so forth.

The ninth stage is manual labeling, at this stage each tweet is given a label whether included in the positive label or negative label with the number of labeling for each positive label and negative label of 55 labels. The results of the positive label and negative negative label are then compared, if the positive label is more than the negative label, then the tweet is included in a positive tweet or class, and vice versa. The amount of data changes from the first stage to the last stage are presented in Table III.

TABLE III. Preprocessing

Preprocessing	Amount of tweet	
	Gojek	Grab
Filtering	56184	45533
Remove Duplicates	51629	40402
Converting Emoticon	51629	40402
Case Folding	51629	40402
Remove Url	51052	40015
Stemming	51052	40015
Remove Stopword	51052	40015
Manual Labelling	51052	40015

C. *Classification*

The dataset of the results of the Preprocessing stage will be divided into testing data and training data. The division of data is determined based on the number of datasets in the driver and the number of datasets in the company. The data distribution for drivers is determined as many as 500 data testing and the rest is for training, while the data sharing for companies is determined as much as 1000 data for testing data and the rest is for training data. The division of data for drivers and companies is presented in table IV and table V.

TABLE IV. Dataset Driver

Driver	The amount of data		Total Dataset
	Data Training	Data Testing	
Gojek	2433	500	2933
Grab	1960	500	2460

TABLE V. DATASET COMPANY

Company	The amount of data		Total Dataset
	Data Training	Data Testing	
Gojek	8979	1000	9979
Grab	6923	1000	7923

Classification tests using Naïve Bayes were performed once. Table VI shows that for the driver of the object found 3 negative class data that were predicted as positive, while for Grab driver found 2 data in the positive class that were predicted as negative.

Table VII shows that for gojek companies found 1 negative class data that was predicted as positive, and 1 positive class data predicted as negative, for Grab companies found 1 data in the positive class that was predicted as negative.

TABLE VI. DRIVER PREDICTIONS

Predictions	Class			
	Gojek		Grab	
	Positive	Negative	Positive	Negative
positive	118	3	114	2
negative	0	379	0	384

TABLE VII. COMPANY PREDICTIONS

Predictions	Class			
	Gojek		Grab	
	Positive	Negative	Positive	Negative
positive	399	1	397	0
negative	1	599	1	602

Tabel VIII hasil klasifikasi untuk *driver* Gojek menunjukan nilai *accuracy* sebesar 99.40%, *precision* sebesar 97.52%, *recall* sebesar 100% dan *error rate* sebesar 0.60%, sedangkan hasil klasifikasi untuk *driver* Grab menunjukan nilai *accuracy* sebesar 99.60%, *precision* sebesar 100%, *recall* sebesar 98.28% dan *error rate* sebesar 0.40%. Hasil klasifikasi untuk *driver* dapat disimpulkan bahwa *driver* Grab lebih baik daripada *driver* Gojek berdasarkan nilai *accuracy* yang menunjukan bahwa nilai *accuracy* untuk Grab lebih besar daripada nilai *accuracy* untuk Gojek.

Tabel IX hasil klasifikasi untuk perusahaan Gojek menunjukan nilai *accuracy* sebesar 99.80%, *precision* sebesar 99.75%, *recall* sebesar 99.75% dan *error rate* sebesar 0.20%, sedangkan hasil klasifikasi untuk *driver* Grab menunjukan nilai *accuracy* sebesar 99.90%, *precision* sebesar 100%, *recall* sebesar 99.75% dan *error rate* sebesar 0.10%. Hasil klasifikasi untuk perusahaan dapat disimpulkan bahwa *driver* Grab lebih baik daripada *driver* Gojek berdasarkan nilai *accuracy* yang menunjukan bahwa nilai *accuracy* untuk Grab lebih besar daripada nilai *accuracy* untuk Gojek.

Nilai *accuracy* dijadikan acuan sebagai hasil akhir dari klasifikasi karena *accuracy* adalah prediksi tingkat kedekatan antara algoritma yang digunakan dengan nilai asli. Hasil dari klasifikasi *driver* dan perusahaan dipaparkan dalam tabel VIII dan tabel IX.

TABLE VIII. CLASSIFICATION OF DRIVERS

Driver	Accuracy	Precision	Recall	Error Rate
Gojek	99.40%	97.52%	100%	0.60%
Grab	99.60%	100%	98.28%	0.40%

TABLE IX. CLASSIFICATION OF COMPANY

Company	Accuracy	Precision	Recall	Error Rate
Gojek	99.80%	99.75%	99.75%	0.20%
Grab	99.90%	100%	99.75%	0.10%

D. Calculation of Net Brand Reputation (NBR)

Welding to determine whether the tweet is included in a positive or negative tweet is done when in the manual labeling preprocessing stage. The total tweets for Gojek and Grab are presented in table X.

TABLE X. NET BRAND REPUTATION

Tweet	Driver		Company	
	Positive	Negative	Positive	Negative
Gojek	616	2317	3560	6419
Grab	594	1866	3516	4407

Net Brand Reputation (NBR) calculation results for drivers with a value of -58% for Gojek and -52% for Grab, while the results of the calculation of NBR for companies with a value of -29% for Gojek and -11% for Grab. Calculation results for drivers and companies are presented in Figure 3.

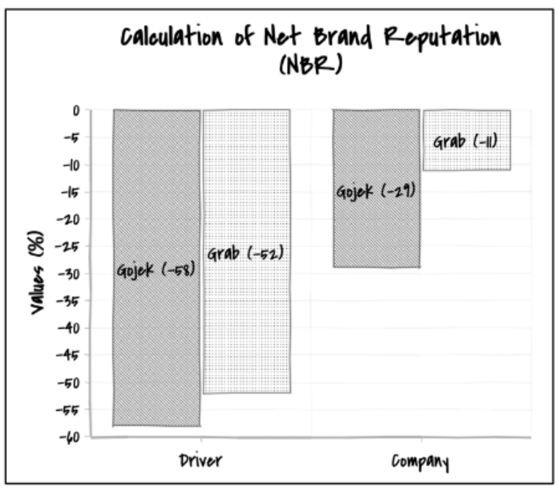

Fig. 3 NBR calculation for Gojek and Grab

Based on Figure 3 that can be seen, both of them produce negative values, which means that Gojek and Grab are still lacking in service. Both the driver and the two companies.

V. CONCLUSIONS

Based on the results of the classification and the results of NBR calculations, it can be concluded that Grab has a better level of user satisfaction when compared to Gojek. This result could have happened because the amount of Grab data was less than Gojek, the withdrawal of data at a certain time affected the classification results and the calculation results of NBR, because at that time either Gojek or Grab received a satisfied or dissatisfied response from the user based on the services provided. , or indeed in reality Grab is better than Gojek.

Suggestions for further research by adding data from two or several different social media such as Twitter and Facebook. Add preprocessing to fix nonstandard words to become standard to maximize the dataset that will be used in NBR calculation and classification and to do classification testing more than once with different amounts of training data and testing data.

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