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Comparison analysis of social influence marketing for mobile payment using support vector machine

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Abstract

There are many digital-based financial services today, one of them is mobile payment service. Users can deposit money and make online transaction with their smartphone through mobile application. Five mobile payment service providers with the most users in Indonesia, according to Dailysocial are GOPAY, OVO, LinkAja, DANA, and PayTren. This study uses sentiment analysis to classify user's opinion into positive and negative classes. The classification method used is Support Vector Machine. This study utilizes three metrics, namely Net Sentiment, Share of Voice, and Social Influence Marketing Score. Those metrics are useful for knowing reputation, reach, and influence of brands in social media. The findings in this study indicate that GOPAY, OVO, DANA, and PayTren have a positive dominant sentiment, while LinkAja has a negative dominant sentiment. The brand with the biggest influence and reaches in the mobile payment industry is GOPAY. While the highest reputation brand is PayTren. The implication of this research is to encourage mobile payment providers to be able to monitor their brand conditions among their competitors by utilizing social network analysis method.

1. Introduction

Among the several categories of the digital industry, financial technology is said to be the fastest growing in recent years. Especially in the mobile payment sector, which has more and more users along with the development of smartphone users. Also, mobile payment is very useful and easy to use in making payments for daily needs [1]. Mobile payment is a method of payment made through mobile devices such as smartphones or tablets, where transaction can be made anywhere and anytime online [2]. Mobile payment that can be used online is part of electronic money services.

There are 36 companies that provide electronic money services in Indonesia which are divided into two types, namely chip-based electronic money services and server-based electronic money services [3]. Mobile payment application is included in server-based financial service type. Considering the number of companies that provide mobile payment services, DailySocial conducted a survey to get the most popular mobile payment service providers and it concluded that the most popular mobile payment providers in Indonesia are GO-PAY, OVO, TCASH, DANA, and PayTren [4]. The five mobile payment service providers use various media to market their products, one of the media used by mobile payment service providers is social media.

Social media is used by costumers to share text, images, audio, and video with other consumers [5]. There are 150 million active users of social media in Indonesia and 52% of them are Twitter users [6]. Data from Twitter can be further processed and can be implemented into organizations for economic needs as well as for job welfare [7]. According to Moro et al. utilization of data that has been processed can have a beneficial impact on marketers to plan marketing strategies [8]. In addition to making business strategies, implementing data that has been processed can help improve the ability to understand customer needs, explore new markets, increase inventory turnovers, reduce customer complaints, and increase staff productivity and efficiency [9]. This data can help to enhance decision making and extracting unforeseen insight and knowledge [10]. By implementing this data, companies can make information about economic and social data as an advantage [11]. To utilize this data, companies need to use some performance metrics to get insight from social media engagement in building a brand [12].

One of the metrics is the Social Influence Marketing Score (SIM Score). SIM Score calculate the influence and condition of a brand in social media. SIM Score is made based on the Net Promoter Score (NPS) that has been used in various companies to measure how much influence is given by the brand. SIM Score uses the same basis as NPS, which is interaction among consumers [13]. This study using SIM Score as a method to calculate the influence and condition of the brand on social media because research on SIM Score is still rarely done. To utilize SIM Score, conversation data crawled from Twitter must be classified into positive and negative sentiments. This study use Support

Vector Machine classification model to predict those data as positive or negative sentiment [14]. The results of the metrics calculation and sentiment analysis can help in optimizing corporate communication on social media, which is an important role to achieve a stable audience growth and can generate monetary profit [15]. There are several studies related to this research and used as a reference for conducting this research.

This research take reference from Kubina et.al. findings about the benefits of big data as a company's tool for understanding consumer behavior [16]. So, this research implements the theory of Kubina et.al. that utilizes big data as an advantage and increases understanding of the consumers. This research also using Vidya et.al. findings about comparation Naïve Bayes, Support Vector Machines, and Decision Tree model, as the metric for net brand reputation in social media and concluded SVM as the best technique [14]. Therefore, this research uses SVM to process the data. However, different from Vidya et.al that using net brand reputation as a metric to measure brand reputation, this research decide to use SIM Score to find out influence of the brand and has two attributes, namely reach and likeability. According to Benglu & Onayli , the SIM Score is a social media metric that can help the company's growth [17]. The explanation from Benglu & Onayli is related to Kubina et al. findings which proves that big data can be used as advantage for company's growth, one of the uses of big data is by using SIM Score. In addition, the two attributes on the SIM score can also be used by the company. Reach to see brand reach, and likeability to see brand reputation. According to Sung-Wook & Jeong explained the importance of brand reputation for the company [18], where high and low of brand reputation would affect consumer purchase intentions. So, likeability can be used by companies to see the value of brand reputation and from this value companies can see how much consumer purchase intention towards the product.

Therefore, this research was conducted to see the influence of five brands in the mobile payment industry on social media using SIM Score. The use of SIM Score as a tool to see the influence of brands in the industry, the owners of five mobile payment brands can use it to make a business strategy to compete with the competitors. Also, brand owners can take advantage of opinions from sentiment analysis results to see detail insights about product weaknesses and strengths, so that brand owners can make product improvements based on these opinions [19]. Several theories are used as the basis for forming SIM Score. The first theory used to form SIM Score is the brand [13].

Brand is the name, term, sign, symbol, design, or combination of them to identify goods or services of the seller from competitors [5]. The brand also states the quality and consistency of the product. Consumers who always buy a product with the same brand will know that they get features, benefits, and quality every time they buy [20]. Brands become an important asset for marketing because brands provide a competitive edge to make company profits [18]. To make a brand profitable for the company, brand reputation is needed to improve the quality of a brand.

Brand reputation is an innate clue that influences consumers' purchase intentions when consumers lack knowledge of the product or feel uncertain about what they will get. Brand reputation acts as an intrinsic guide to the product or service and brand reputation reduces the risk of the product or service [18]. Brand is used as a measurement target in the SIM Score so that it is necessary to collect data to measure the brand. Measuring brand reputation in social media can use data mining as a recent method.

Data mining is the process of finding patterns in data that can be done automatically or semi-automatically [21]. One specific area of data mining is text mining. Text Mining is the process of finding patterns in text data, by extracting information that is useful for certain purposes. Text data is unstructured, formless, and difficult to deal with. By using text mining, information in the text can be extracted clearly and explicitly [21]. Data that has been extracted can be processed using sentiment analysis to evaluate people's opinion through a conversation.

Sentiment analysis is a field of study to analyze people's opinions, sentiments, evaluations, assessments, attitudes, and emotions towards products, services, organizations, individuals, issues, events, topics, and attributes of these entities [22]. In addition to the field of study, sentiment analysis can also be used in fields such as consumer information, marketing, books, applications, websites, and social. The main purpose of analyzing sentiments is to analyze opinions and see the score of these sentiments [23]. Sentiment analysis usually can be classified into two classes, positive and negative. To classify into two classes, it is necessary to use classification methods such as Naïve Bayes, Support Vector Machine, and Senti-Lexicon [22].

This research uses Support Vector Machine as a classification method. Support Vector Machine (SVM) is one part of data mining which is a technique for making predictions, both in regression and classification, to get the separator function (hyperplane) to separate different target variable values [24]. SVM can classify data linearly or linearly separable and non-linear or nonlinear separable [25]. This study uses linearly separable data where the data can be separated linearly.

Linear data in the SVM algorithm looks for hyperplane with the largest margin. The best hyperplane not only separates data well but also has the largest margin. Data that is on this hyperplane is called support vector [25]. SVM has an effective and smooth polarity detection in doing classification depending on the ratio of training and testing data provided [26]. SVM processing results can be used as insight for the company to see the performance of the company [27]. When the data has been collected and further processed into sentiment data, it can be used as a basis for determining SIM Scores.

Social influence marketing is a marketing technique that uses social media and influencers to achieve an organization's marketing and business needs. The essence of social influence marketing is about recognizing, calculating, and utilizing the fact that when potential customers make purchasing decisions, customers are influenced by various people through conversations that customers have with them online [13]. Social influence marketing has a measurement tool to measure the influence and condition of a brand, namely Social Influence Marketing score (SIM Score).

SIM Score is a measuring tool that can recognize the influence of a brand compared to competitors. SIM Score can be used as a reference to determine the condition of a brand on social media. With knowing SIM Score, brand owners can find out the condition of a brand in the eyes of consumers that can be used to develop marketing strategies. SIM Score calculates two important attributes that reach and likeability. Reach is used to determine the extent of reach for a brand, while likeability is used to find out how the reputation of the brand [13].

2. Research Method

This research uses a quantitative method that is a research method based on the philosophy of positivism which is used to examine populations or certain samples with sampling techniques that are usually taken randomly, and collecting data using quantitative research instruments [28]. Based on the objectives, this research belongs to the type of descriptive research. Descriptive research is designed to collect data and describe the characteristics of a person, activity, or event [29]. Based on the time of implementation, this research is included in the cross-section research, which is a research that collects data in one period, then the data is processed, analyzed and drawn conclusions [30]. The steps to analyze data in the study are as follows:

1. Data Collection

This study using RStudio to collect data from Twitter with keyword related to brand GOPAY, OVO, LinkAja, DANA, and PayTren. The data was crawled from May 1 to May 31, 2019. This research obtained 344.969 data raw from each brand.

The data that already collected should be processed to preprocessing data, so the data that has a lot of noises can be cleansed. Preprocessing data has several subprocesses such as transform cases, tokenize, filter tokens, stopwords, and steming, these subprocess is perform automatically using Rapidminer [26]. Before the data is cleaned automatically, it is necessary to label positive and negative sentences. The data that will be labelled has to be cleansed from the links, unique codes, duplicates, and usernames. Data labeling is conducted with three people with different academic background and based on the meaning of positive and negative words in Indonesian [31]. This process is carried out so that the data can be processed by the model.

After preprocessing data, 28,189 data were obtained and the next step is to perform sentiment analysis in Rapidminer using the SVM method.

2. Sentiment Analysis

Sentiment analysis is carried out to determine the extent to which the model can classify and predict well. Sentiment analysis will be using the SVM method because based on Vidya et.al. research SVM is the best clasifier model compared to naïve bayes and decision trees [14]. The results of sentiment analysis produce a confusion matrix which is used to determine the accuracy, recall, and precision of the classification method used. The accuracy value is useful for knowing the level of closeness. The recall value is useful for knowing the level of success. The value of precision is used to determine how accurate the data is classified. Accuracy, precision, and recall can be calculated using the following Equation 1, Equation 2, Equation 3, Equation 4, and Equation 5.

Accuracy:
$$\frac{True\ Positive + True\ Negative}{True\ Positive + False\ Negative + True\ Negative + False\ Positive} \tag{1}$$

Precision:

Positive Precision:
$$\frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

Negative Precision:
$$\frac{True\ Negative}{True\ Negative + False\ Negative} \tag{3}$$

Recall:

Positive Recall:
$$\frac{True\ Positive}{True\ Positive + False\ Negative} \tag{4}$$

Positive Recall:
$$\frac{True\ Negative}{True\ Negative + False\ Positive} \tag{5}$$

Accuracy, precision, and recall values are calculated automatically using Rapidminer. This value can be used to determine the performance of the model created in this research. In the distribution of training and testing data ratios, this research conducted experiments on three types of ratios namely 30% training data and 70% testing data, 50% training data and 50% testing data, and finally 70% training data and 30% testing data. The distribution of these three types of data ratios is conducted to determine which ratio has the best model performance, and is used as the main ratio in sentiment analysis [26]. This research uses accuracy to determine which model has the best performance among the three types of ratios [32]. After the data has been classified successfully, the next step is to calculate Net Sentiment, Share of Voice, and SIM Score.

3. Calculating Net Sentiment, Share of Voice, and SIM Score

Net Sentiment is a measurement tool to find out the reputation of an entity on social media using sentiment data associated with that entity [33]. Net Sentiment is divided into two, namely Net Sentiment for the brand and Net Sentiment for the Industry. Net Sentiment for the Brand uses data in a brand, while Net Sentiment for the Industry uses data in industry. The following are Equation 6 and Equation 7 for Net Sentiment for the Brand and Net Sentiment for the Industry.

Net Sentiment for the Brand:
$$\frac{(positive + neutral\ conversations - negative)}{total\ conversations\ for\ brand} \tag{6}$$

Net Sentiment for the Industry:
$$\frac{(positive + neutral\ conversations - negative\ industry)}{total\ conversations\ for\ industry} \tag{7}$$

Net Sentiment equations on positive and neutral conversations are combined because the Support Vector Machine model is a binary classification and refer to previous research by Singh that also merged positive and neutral conversations [13].

After knowing the value of Net Sentiment the next step is to calculate Share of Voice. Share of Voice is all volume mentions in a brand expressed as a percentage of all mentions in the industry [34]. The Share of Voice is as follows Equation 8.

$$\frac{Total\ brand\ conversations}{Total\ brand + total\ industry\ conversations} \tag{8}$$

The next step after knowing the value of Share of Voice is to calculate the SIM Score. SIM Score is a measurement tool to determine the condition and influence of a brand by using Net Sentiment. SIM Score has two important attributes, reach and likeability. To determine the reach, Share of Voice is used. Meanwhile, to determine likeability, Net Sentiment is used. Reach and likeability is determined to find out whether the reach and likeability values are in line with the SIM Score value [13]. SIM Score is determined using the following Equation 9.

$$\frac{Net\ Sentiment\ for\ the\ brand}{Net\ Sentiment\ for\ the\ industry}\ x\ 100 \tag{9}$$

4. Comparison

In the final stage, a comparison between the five most popular mobile payment service provider brands in Indonesia is conducted. Comparisons are made to find out which brand is the most superior among the five brands, refer to the value of Net Sentiment, Share of Voice and SIM Score for each brand.

3. Results and Discussion

The results and discussion consist of sentiment analysis, Net Sentiment, Share of Voice, and SIM Score calculation, and finally the comparison.

3.1 Data Collection

Data collection is perform using Rstudio on Twitter from May 1 to 31 2019 and 344,969 data raw were obtained. This data still has a lot of noise, so this data needs to be cleaned. Table 1 is an example of data raw that has a lot of noise.

The data in Table 1 still has links, unique codes, duplicates, and user names, these noise needs to be removed so that the data can be further processed at the labeling process. After the data is cleansed, data needs to be labeled positive and negative. Data labeling is conducted with three people with different academic background and based on the meaning of positive and negative words in Indonesian. Table 2, is examples of data that has been cleaned and labeled.

Table 1. Data Raw Example

Tweet
@baznasindonesia keren sekali bayar zakat pakai gopay https://t.co/zotscpnkjq
Mantap gaes cuma bayar 20 rb aja di gopay <u+0001f44d><u+0001f3fb><u+0001f60c> https://t.co/gzl32cphgk
Tertipu isi listrik @linkaja katanya cashback nyatanya zonk. Kapok! Mending isi di @tokopedia
@ovo_id pelayananya sangat jelek sekali

Table 2. Labeled Data

Sentiment	Tweet
Positive	Keren sekali bayar zakat pakai gopay
	Mantap Cuma bayar 20 rb aja di gopay
Negative	Tertipu isi listrik katanya cashback nyatanya zonk kapok
	Pelayanannya sangat jelek sekali

After the data was cleaned and labeled as in Table 2, 28,189 data were obtained. However, this data will be cleansed again using Rapidminer. There are several subprocesses to preprocessing data in Rapidminer such as transform cases, tokenize, token filter, stopwords, and steming. This subprocess is done automatically and will be directly connected to sentiment analysis. So, after preprocessing, the next step is to do sentiment analysis.

3.2 Sentiment Analysis

Before performing sentiment analysis for each brand. all data will be merged and will be divided into three types of data ratios of training data and testing data ratios, namely 70:30, 50:50, and 30:70. After the data is separated into three types of ratio data, an experiment will be conducted on the three data to find out which ratio has the best model performance to do sentiment analysis using SVM method [26]. This research uses the SVM method based on the study of Vidya et.al. which states that SVM method has the best performance compared to Naïve Bayes and decision trees [14]. And to determine the best ratio, accuracy is used as the basis for determining the performance of the model [32].

Table 3. Three Types of Ratio Data

Ratio (training data : testing data)	Accuracy	Precision		Recall	
		Positive	Negative	Positive	Negative
30% : 70%	73.84%	72.88%	76.26%	88.53%	52.79%
50% : 50%	74%	73.17%	76.12%	88.62%	52.74%
70% : 30%	77.03%	76.65%	78.21%	91.56%	52.05%

The results of the data processing in Table 3 obtained a ratio of 70% training data and 30% testing data, has the best performance compared to the other two ratios [35]. At the ratio of 70%: 30% shows the highest level of accuracy compared to the ratio of 50%: 50% and the ratio of 30%: 70%. This mean the model that uses a ratio of 70% training data and 30% testing data has better performance than the other two ratios [32]. Based on these results a ratio of 70% training data and 30% testing data was chosen as the basis for sentiment analysis for each brand.

Table 4. SVM Classification Results for Each Brand

Brand	Accuracy	Precision		Recall	
		Positive	Negative	Positive	Negative
GOPAY	77.30%	76.28%	85.75%	97.78%	30.49%
OVO	80.71%	85.79%	79.1%	56.43%	94.63%
LinkAja	80.56%	82.61%	79.04%	74.54%	85.95%
DANA	79.75%	78.56%	82.36%	90.7%	63.68%
PayTren	80.82%	79.5%	93.55%	99.17%	32.04%

From Table 4, it shows that the model for the PayTren brand has the highest accuracy rate, that means the level of closeness of the predicted value and the actual value in the PayTren data is 80.82%. Whereas in the GOPAY brand model has the lowest level of accuracy among the other models. It means the level of closeness of the predicted value and the actual value in the GOPAY brand is the lowest.

After knowing the level of model performance in each brand, the training and testing data are combined to calculate positive and negative sentiment. From this dataset, total sentiments were obtained for the GOPAY, OVO, LinkAja, DANA, and PayTren brands that can be seen in Table 5.

Table 5. Total Sentiment

Sentiment	GOPAY	OVO	LinkAja	DANA	PayTren
Positive	7412	6398	1831	2534	724
Negative	2598	3072	1949	1449	222

In Table 5 it is known that GOPAY, OVO, DANA, and PayTren brands have dominant positive sentiment, while the LinkAja has a dominant negative sentiment**.** That means in the GOPAY, OVO, DANA, and PayTren have more consumers having positive opinions about the brand, while in the LinkAja consumers have more negative opinions about the brand. The next step is to calculate the Net Sentiment, Share of Voice, and SIM Score.

3.3 Net Sentiment, Share of Voice and SIM Score Results

After performing sentiment analysis, the next step is to use sentiment data as a basis for calculating Net Sentiment, Share of Voice, and SIM Score. This step is carried out to determine the influence, reach, and reputation of the company [13]. Table 6 shows the results of calculations of Net Sentiment, Share of Voice, and SIM Score:

Table 6. Calculation Results

Brand	Share of Voice	Net Sentiment for Brand	SIM Score
GOPAY	26.2%	48.1%	50.09
OVO	25.1%	35.1%	34.61
LinkAja	11.82%	-3.1%	-1.22
DANA	12.38%	27.2%	11.29
PayTren	3.24%	53%	5.22

Net Sentiment calculations are divided into Net Sentiment for the Brand and Net Sentiment for the Industry. In Net Sentiment for the Brand calculations are carried out using only brand scope, while Net Sentiment for the Industry uses the scope of all direct competitors. The results of the Net Sentiment for the Brand calculation can be seen in Table 6. In Table 6, it can be seen that the highest Net Sentiment for the Brand value is the PayTren brand, which means PayTren has the best reputation among its competitors. GOPAY has the second highest reputation, followed by OVO and DANA. Meanwhile, LinkAja has the lowest reputation among its competitors. After obtaining the Net Sentiment for the Brand value, it is necessary to determine the Net Sentiment for the Industry. Net Sentiment for the Industry calculation result obtained a value of 34.08%, this means that as many as 34.08% of opinions have a positive sentiment about the mobile payment industry from those five brands.

After calculating Net Sentiment, the next step is to calculate the Share of Voice. Share of Voice is used to calculate all mentions on a brand and expressed using percentages. Besides, Share of Voice can be used to find out the reach of each brand in the industry. From Table 6, it can be seen that GOPAY has the largest reach in the mobile payment industry, while PayTren has the lowest reach in the mobile payment industry. The Share of Voice value also reflects the volume of data owned by the brand.

The last step is to calculate the SIM Score. that used to determine the condition and influence of the brand. SIM Score is obtained by dividing Net Sentiment for the Brand and Net Sentiment for the Industry. Net Sentiment values are divided not in percentage terms. The SIM Score calculation results can be seen in Table 6. It can be seen that GOPAY has the highest SIM Score, which means that GOPAY has a great influence on Twitter compared to other mobile payment brands. While LinkAja has the lowest value among the five brands, this means that LinkAja has the smallest influence on the mobile payment industry.

3.4 Comparison

After getting the results, Then the SIM Score will be compared and see how much the contribution made by Net Sentiment and Share of Voice in determining the SIM Score. Table 6. described that GOPAY has the highest score on the SIM Score. Net sentiment and Share of Voice are greatly contribute to generate the SIM Score, making GOPAY become the most influential brand in the industry. OVO became the most influential brand after GOPAY followed by

DANA. Meanwhile, PayTren has the lowest Share of Voice but high Net Sentiment, it still resulted in a low SIM score. LinkAja has negative value for Net Sentiment, so it has negative value for SIM Score too, although its Share of Voice is bigger than PayTren.

Based on research results, the highest SIM Score in the mobile payment industry is GOPAY. Therefore, OVO, LinkAja, DANA, and PayTren Brands that have a lower value than GOPAY can utilize these insights to enhance the features they have. In the case of GOPAY and OVO, the high value of Share of Voice and Net Sentiment greatly contributes to determine the SIM Score. In the case of DANA and PayTren, the value of Share of Voice smaller than Net Sentiment affecting the SIM Score calculation results becomes smaller. For LinkAja, that has good value in Share of Voice, but because the Net Sentiment has negative value, so the SIM Score also becomes negative. We can conclude that in determining the Social Influence Marketing Score, it is not enough to only has a high Net Sentiment but also require a high Share of Voice.

The results of this study can be used as an insight into the organization or company to help marketing activities [19]. To improve features and set prices according to the features, the mobile payment providers can use consumer opinion on the results of sentiment analysis to find out the advantages and disadvantages of its products. Also, brand owners can utilize the SIM score to make decisions in advertising their products by looking at the value of the Share of Voice [9]. Brand owners can also use Net Sentiment to approach consumers depending on their reputation to build the brand and decrease the complaint [12].

4. Conclusion

Sentiment analysis using the Support Vector Machine method with a ratio of training data and testing data of 70%: 30% has better performance than 50%: 50% or 30%: 70% to classify data on all five mobile payment service providers. This result is based on a model with 70%: 30% ratio data which has a higher level of accuracy compared to the other two ratios. In addition, the results of sentiment analysis on each brand indicate that PayTren has the best performance from level of accuracy that it has, while GOPAY has the lowest performance from the level of accuracy. Based on the dominant sentiments of GOPAY, OVO, DANA, and PayTren have positive dominant sentiments, while LinkAja has negative dominant sentiments. It shows that GOPAY, OVO, DANA, and PayTren get more positive conversation from customers in social media, different with LinkAja that has more negative opinion from its customers.

From the results of sentiment analysis, we can calculate SIM Score, Net Sentiment, and Share of Voice. And the result of calculations is GOPAY has the highest value on SIM Score and Share of Voice, while PayTren has the highest Net Sentiment. This means GOPAY has the highest influence and widest reach compared to its competitors, while PayTren has the best reputation compared to its competitors.

The results of the Sentiment Analysis, SIM Score, Net Sentiment, and Share of Voice can be used as company insight to improve products depends on the influence, reputation, and opinion on sentiment analysis. as a material consideration for decision making in determining strategies to fight competitors. To make decisions in advertising their products based on the value of the Share of Voice. And to approach consumers depending on influence and reputation that the brands have.

This research has limitation in comparing SIM Score where the datasets for each brand does not have same size. For further research, we suggest testing the SIM Score comparison using a similar number of datasets for each brand to obtain equal value of Share of Voice. Then, the SIM Score can be analyzed with more balanced.

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