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Original Research

Analysis of Emotional Aspect of Twitter Postings about Large Scale Social Limitations in Suppressing the Spread of COVID-19

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Abstract

The spread of COVID-19 has recently become a public concern. There are many public emotions regarding implementing the Large-Scale Social Restrictions (PSBB), which was especially implemented in Jakarta, first implemented in Indonesia. People have various emotions mirroring their tweets in making statements on social media, especially Twitter. Emotional expressions can be joy, sadness, anger, and fear. This study aims to determine the impact of the implementation of PSBB in reducing the spread of COVID-19 on people's emotional factors on Twitter. The method used in this research is the SentiStrength method and Support Vector Machine. Furthermore, the comparison between the two methods is completed to determine which one is better. The tweet data used were 12,735 lines from 10 April 2020 to 21 August 2020. The highest accuracy achieved of SentiStrength and SVM is 88.33% and 73.33%, respectively. Similarly, f-measure of SentiStrength (88.14%) outperforms SVM (75%). This research shows that the implementation of PSBB on public emotional factors on Twitter is that happy emotions with the highest sentiment are positive sentiments, reaching 5246 sentiments.

Keywords: Large-Scale Social Restrictions, Emotional Factors, COVID-19, Twitter, Social Media, Indonesia.

Introduction

With the rapid development of information technology, many have changed the way humans communicate with each other. Large amounts of textual data are generated every day. It is estimated that 80 percent is unstructured data (Debortoli, Müller, Junglas & vom Brocke, 2016). Data is generated via the internet, mainly through social networking sites and online chat applications. On the Amazon.com page, more than 140 million customer comments on nine million products by millions of Amazon customers (McAuley, Pandey & Leskovec, 2015; McAuley, Targett, hi Javen & Hengel Van Den, 2015). On social media Twitter, an average of

500 million tweets are generated per day from 300 million active users (Debortoli et al., 2016). This abundance of data can create new opportunities for quantitative and qualitative information systems researchers (Nagarajan & Gandhi, 2018).

The general public widely uses social media. Many people use social media to express their opinions, experiences, and other concerns (Troussas, Virvou, Espinosa, Llaguno & Caro, 2013). That statement is an understanding of sentiment. Sentiment analysis is a text classification that involves natural language processing, machine learning, data mining, information retrieval, and other research areas. In addition, sentiment analysis can be divided into news comment analysis (Xu, Meng, Qiu, Yu & Wu, 2019), product comment analysis, and movie commentary analysis (Tseng, Chou & Tsai, 2018).

Since the enactment of Large-Scale Social Restrictions (PSBB) in Jakarta on 10 April 2020, it is hoped that the spread of COVID-19 will decrease. According to the Ministry of Health of the Republic of Indonesia and the World Health Organization (WHO), the number of confirmed positive people for COVID-19 in Indonesia was 452,291 cases as of 11 November 2020 (WHO, 2020). Jakarta Province occupies the top rank in the number of people confirmed positive for COVID-19 with 114,343 cases as of 11 November 2020. Per day, the increase in positive cases in Jakarta is on average over 1,000 cases (Gugus Tugas Percepatan Penanganan COVID-19, 2020).

Large-Scale Social Restrictions or PSBB are restrictions on certain activities of residents in an area suspected of being infected with Corona Virus Disease 2019 (COVID-19) in such a way as to prevent the possible spread of Corona Virus Disease 2019 (COVID-19) (Kementrian Kesehatan Republik Indonesia, 2020). The spread of COVID-19 has recently become a public concern. There are many public sentiments regarding the implementation of the PSBB, which was especially implemented in Jakarta which was implemented for the first time in Indonesia. The PSBB in Jakarta immediately became the main topic in any discussion in the community, for example, through television media, online news, and social media. Social media is a free and poorly filtered source of information dissemination, and sometimes bad information is often spread through social media. Many parties use social media to spread positive and negative news.

The impact of the dissemination of text information on Twitter social media, first the positive impact of the dissemination of tweet text information is that it is easy for us to access and retweet to others so that information is very easily spread, and also important information can be obtained immediately, for example, disaster information, product information, and also much information that has a positive value. The two negative impacts of disseminating tweet text information include spreading fake news/information and fraud. The impact of positive and negative information itself can affect individuals and groups who have accessed the information. The plan to relocate the capital city greatly impacts information dissemination, especially from social media, because almost all information is spread easily.

Making a statement on Twitter is called a tweet, and there are various emotions from the community who wrote the tweet. Emotional expressions can be joy, sadness, anger, fear, surprise, and disgust. The expression of these emotions is interesting to study further, wherein expressing these emotions and people experience an event that can cause emotions (Mohamed Shakeel & Baskar, 2020). These six emotions are the most basic ones in humans (Mohamed Shakeel & Baskar, 2020) and are suitable for this study. This study uses the Sentistrength and Support Vector Machine (SVM) method. The Sentistrength method is a Lexicon-based method.

The SVM method is a method that is included in the Supervised Learning method (Muhammad, Mushtaq, Junejo & Khan, 2020). With the emotional impact of the community on Twitter regarding the implementation of PSBB in Jakarta, it is hoped that it can have a psychological impact on government policies in handling COVID-19 so that it can be considered in the implementation of future policies.

Literature Review

Rezwanul and Rahman (2017) developed a classification method that can accurately and automatically classify the sentiments of unknown tweets. This research proposes a method used to classify sentiment classes accurately. The method introduced is the sentiment classification algorithm (SCA) based on the k-nearest neighbor (KNN) and SVM. With the results of the SCA method, it is more accurate to use than the KNN and SVM methods. However, this research can only use tweet data in English and has not reached tweets containing emoticons.

Another research, as in reference (Putra, Pranowo & Setyohadi, 2020), aims to analyze all the tweet information obtained from Twitter, divided into positive and negative classes, to predict presidential candidates' electability. This study's classification process uses the Lexicon-Base and Support Vector Machine (SVM) method. The results were positive 24.10%, negative 38.30%, and neutral 38.30% for the keyword Jokowi, while Prabowo got a positive percentage of 0.20%, negative 0.10%, and neutral 0.70%. The only drawback is that there is no sentence normalization for non-standard words.

Analysis of the support sentiments of political parties during the general elections in Spain on Twitter becomes the concern of another research (Franco-Riquelme, Bello-Garcia & Ordieres-Meré, 2019). The data obtained is determined using geolocation parameters to obtain data according to the desired location. This research proposes a support indicator, namely the positiveness ratio (PR), which is used as a reference in determining the sentiment analysis results. The results show that the proposed indicators can show the pattern of political party support tendencies.

Lastly, another research deals with analyzing the relationship between sentiments on Twitter and the rise or fall of the stock prices (Pagolu, Reddy, Panda & Majhi, 2016). In this research, several methods are used, namely Random Forest, SMO, Logistic Regression, and LibSVM. News indirectly affects people's investment in a particular stock and will increase the stock price. The results show a strong correlation between the ups and downs of stock prices with public sentiment on Twitter. The contribution of this research is the development of a sentiment analyzer that can assess the type of sentiment in a tweet.

Materials and Methods

Figure 1 explains the research methodology used in this study. It explains the stages of research from literature study to the stage that produces an analysis sentiment based on emotional aspects.

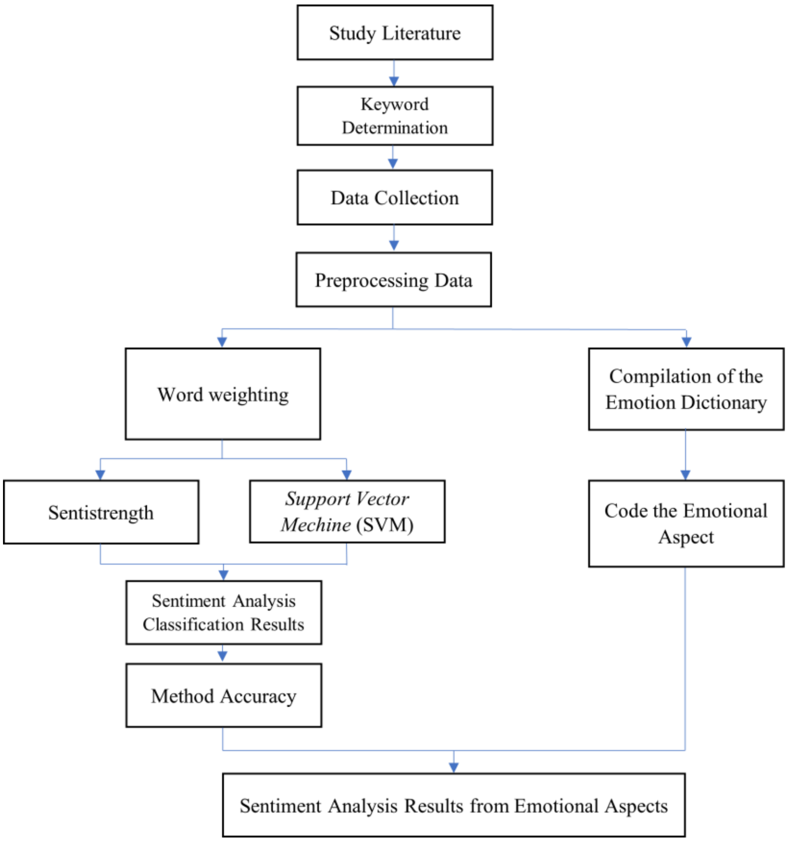

Figure 1: Research Methodology Schemes

After the pre-processing process, word weighting was carried out using the SentiStrength and TF-IDF methods. In data processing, there are two methods used, namely the SentiStrength and SVM methods; in each of these methods, the sentiment is obtained from the data that has been processed; after that, the accuracy of each method is calculated, the sentiment results are obtained from an emotional aspect. Compiling an emotional dictionary is carried out before analyzing sentiment from the emotional aspect, then coding each emotional aspect, and then obtaining the final sentiment results. The method with the highest accuracy will be discussed.

Data Collection

For doing data collection or what is commonly called the data mining/text mining process, the python 3.7 software application is used from the github.com/Jefferson-Henrique/GetOldTweets-python account with the downloaded folder and then put in the D: directory, which uses the Python programming language. The program is then modified, especially how the data is saved into a file. After the modification, the program can directly insert the data into a CSV file that has been previously set in the D directory.

Data Preprocessing

In the data pre-processing process, the aim is that the data will be cleaner, and the results of the sentiment analysis will be better and speed up the data processing process when the data enters the analysis stage. The steps are discarding meaningless or repetitive data, checking inconsistent data, and correcting incorrect data if a typo occurs. Here are the steps in pre-processing:

1. Remove symbols such as hashtag (#), URL, and mention (@).
2. Lowercase is the process of changing the content of someone's tweet; originally, there are uppercase letters changed to lowercase letters.
3. Stop word removal is a process wherein it removes a word that is not required in classification. The words will be processed and seen in a dictionary whether the words have any meaning or not.
4. The pre-processing process is complete.

Coding Process

Data processing in this study has several stages, data cleaning using NetBeans. Proceed to the word weighting stage using PyCharm, coded for word weighting. In word weighting, a dictionary contains words that have been assigned numerical weightings. Give weight to words based on the positive or negative of a word. The next stage is to determine the sentiment of a sentence based on the weight of each word. The final stage is to classify the sentences that have received the sentiment into 6 existing emotional aspects.

Classification of tweets into Sentiment Analysis

After the previous stage is completed, the data is processed. The sentiment classification consists of positive, neutral, and negative sentiments. Word weighting in the Sentistength method is exemplified in Figures 2 and 3.

```
suka bingung gak sih jokower yg suka bikin hastag menghina anies
psbb gagal psbb jakarta kacau dll kalo penanganan epidemi pusat
udh bener bisa dimaklumin lah   lah sama2 gagal wkwk
```

Figure 2: Unweighted Tweets

The PyCharm application accomplishes the weighting process to these tweets. Finally, the results are shown in Figure 3.

```
suka [4] bingung [-3] gak sih jokower yg suka [4] bikin hastag
menghina [-4] anies psbb gagal [-5] psbb jakarta kacau [-4] dll kalo
penanganan epidemi [-3] pusat udh bener bisa dimaklumin lah lah
sama2 gagal [-5] wkwk
```

Figure 3: Weighted Tweets

The input tweet means that the sentiment will be given a sentiment value in the program dictionary. The final score that needs to be summarized to conclude that the sentence is positive, negative, or neutral is determined from the maximum positive value and the maximum negative value, while the result label, either positive or negative, depends on the tweet data. This decision is based on the rules for the SentiStrength method below, which are made into 3 rules, namely as follows:

a. If Positive Value > Negative Value, then Positive Sentiment
b. If Positive Value < Negative Value, then Negative Sentiment
c. If Positive value = Negative Value, then Neutral Sentiment

Sentiment Classification to Emotional Aspects

In classifying sentiments into emotional aspects, a dictionary is needed to determine emotional aspects. The dictionary is translated from English to Indonesian, which is the basis for determining the corpus/dictionary. The author also performs n-grams to see what words are contained in the data. So it can add to the dictionary used as a reference. The following is an example of classifying sentiments into emotional aspects in Table I.

Table 1

Examples of classifying sentiments into emotional aspects

Word	Word Weight	Emotion Code
Sukses (Success)	4	1
Gagal (Failed)	-5	2
Pengawasan (Supervision)	-2	3
Bingung (Confused)	-3	4
Semangat (Spirit)	4	5
Perubahan (Change)	4	6

Table 1 is some examples of words for classifying sentiments into the emotional aspects, and the emotional code shown has been explained on the theory put forward by Paul Eckman (Öhman, 1994).

The Accuracy of Sentiment Analysis Method

Several parameters, such as precision, recall, f-measure, specificity, and accuracy, are used to evaluate the method's performance. The following are some formulas used to determine precision, recall, f-measure, specificity, and accuracy. (Muhammad et al., 2020; Bouazizi & Ohtsuki, 2019).

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \tag{1}$$

Precision is the percentage of positive sentiment predictions that are true (true positive) compared to the overall positive sentiment results.

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \tag{2}$$

The recall percentage of positive sentiment predictions (true positive) compared to the correct positive sentiment data.

$$\boldsymbol{F-measure} = \frac{\boldsymbol{2\,.\,precision\,.\,recall}}{\boldsymbol{precision + recall}} \tag{3}$$

F-measure is a comparison between precision and recall.

$$\boldsymbol{accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+FP+TN+FN}} \tag{4}$$

Accuracy is the percentage of correct positive and negative sentiment predictions compared to the overall data.

Information:

TP = True Positive

FP = False Positive

TN = True Negative

FN = False Negative

Result

The data in this study came from Twitter which was taken from 10 April 2020 to 21 August 2020. The data were taken based on tweets containing PSBB Jakarta, PSBB Transisi, and Jakarta Tanggap Coronav keywords. Tweets that were retrieved reached 12.735 rows of data.

Emotions result from physiological conditions that arise from a stimulus in the environment. Emotion occurs after a physiological reaction, meaning that a person perceives a stimulus in a physiological environment and then responds and interprets these physiological changes as an emotion. The following will analyze the emotional aspects of implementing the PSBB in Jakarta based on public sentiment on Twitter. To analyze the emotion of happiness in each phase in the application of PSBB Jakarta, the following is a graphic image of happiness emotions which can be seen in figure 4.

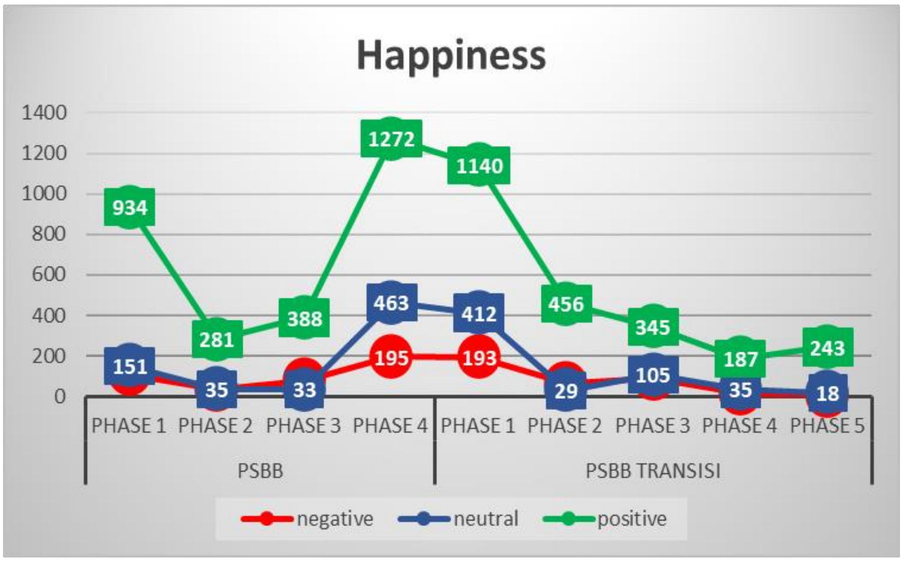

Figure 4: Emotional Happiness Graph

In Figure 4, it can be seen that emotions are happy with positive sentiment in each phase, from the PSBB to the Transitional PSBB, which shows the highest levels of negative and neutral sentiments. In phases 2 and 3, both the PSBB and the Transitional PSBB experienced a decrease in the number of tweets, and in the early and final phases of the PSBB implementation, there was an increase in happy tweet's emotions. News about the spread of COVID-19 has decreased, shared in phase 4 of the PSBB with 1110 retweets and as many as 5936 likes.

To analyze sadness emotions for each phase in the Jakarta PSBB, the following is a graphic of sadness emotions, which can be seen in figure 5.

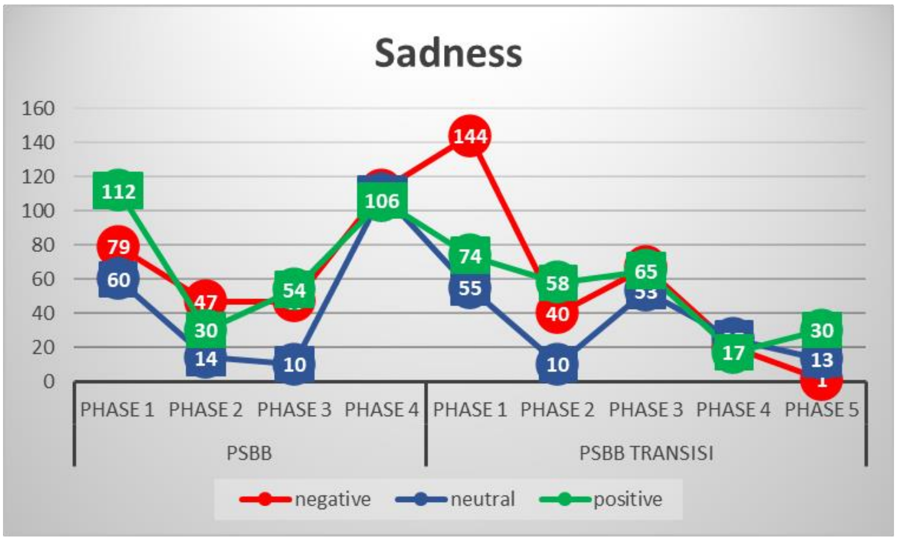

Figure 5: Emotional Sadness Graph

In Figure 5, it can be seen in Phase 1 of the PSBB Transition that negative sentiments have the highest sad emotions. For sad emotions, the graph shown experienced a spike at the beginning and end of the phase in the PSBB and Transitional PSBB. In phase 1 of the PSBB, the transition to negative sentiment was the highest, and this was influenced by the news stating that the implementation of the PSBB failed, which received 18 retweets and 75 likes, many tweets were based on the news so that it affected the sentiment results.

To analyze anger emotions for each phase in the Jakarta PSBB, the following is a graphic of anger emotions that has shown in figure 6.

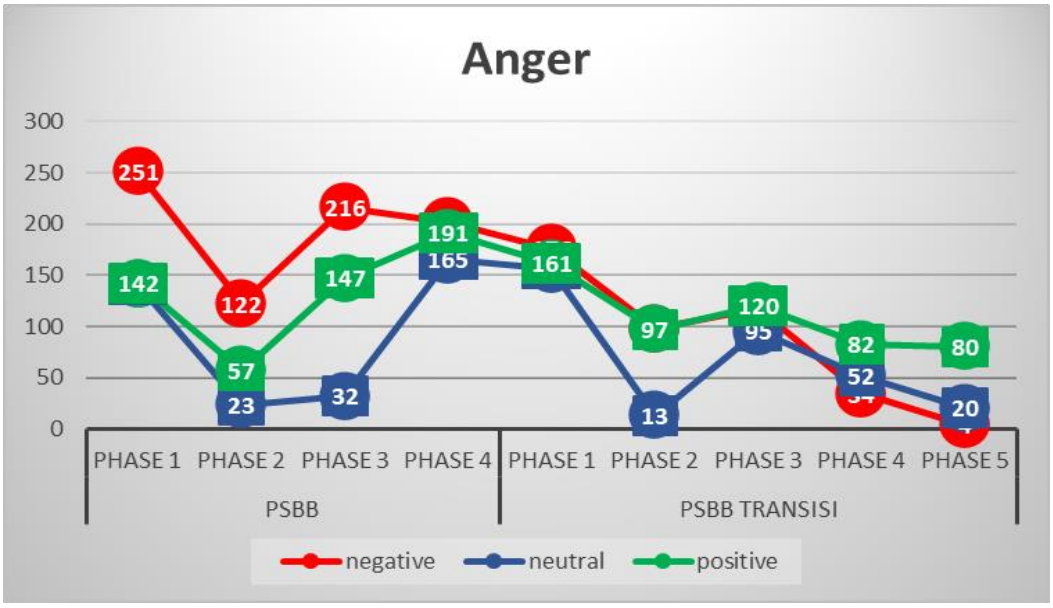

Figure 6: Emotional Anger Graph

In figure 6, it can be seen that at the beginning of the implementation of the PSBB, there was a negative sentiment on angry emotions that could occur because the community did not like the implementation of the PSBB in Jakarta. However, after phase 2 to phase 4, the negative sentiment PSBB experienced a decline, and the Transitional PSBB experienced a decrease in negative sentiment. Several things caused high negative sentiment at the beginning of the implementation of the PSBB. Namely, in the application of the PSBB, there were sanctions given for those who violated the PSBB rules; this announcement immediately gave negative sentiment by retweeted 24 times. After phase 3 of the PSBB, negative sentiment decreased due to praise for the PSBB policy by several considered successful circles, thus suppressing negative sentiment.

To analyze fear emotions for each phase in the Jakarta PSBB, the following is a graphic of fear emotions, which can be seen in figure 7.

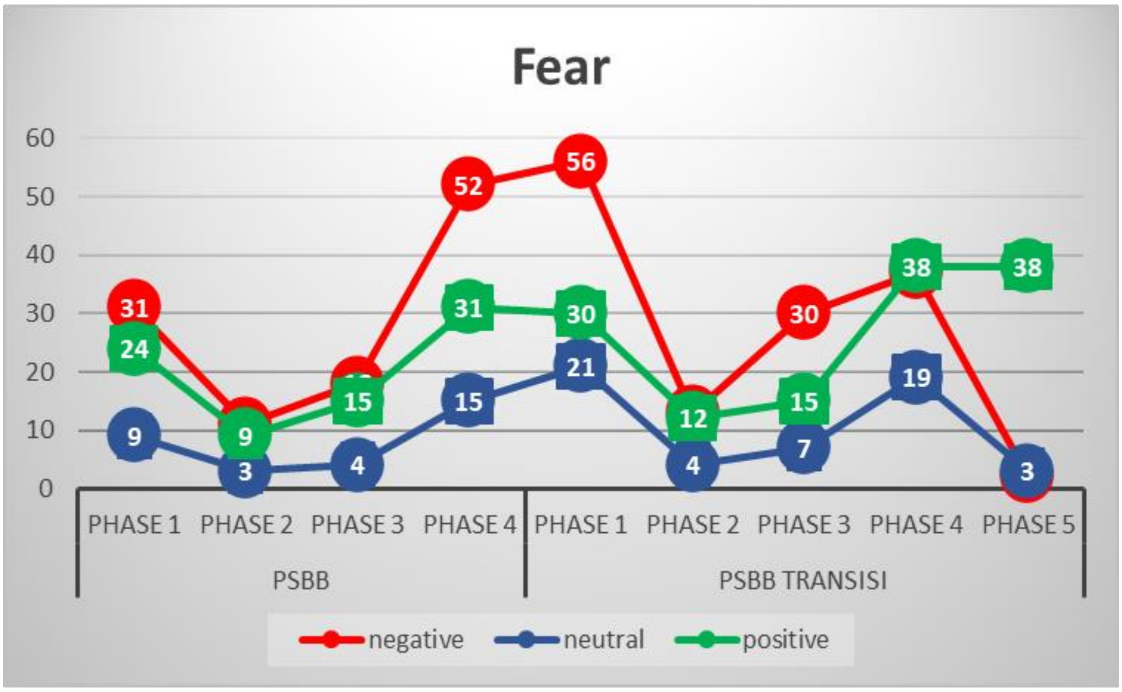

Figure 7: Emotional Fear Graph

In figure 7, it can be seen that the negative sentiment with emotions of fear from the beginning to the end of the PSBB and Transitional PSBB phases is the highest of neutral and positive sentiment. However, the phase 4 Transitional PSBB experienced an increase in positive sentiment. This is due to a decrease in COVID-19 spread in Jakarta, which was retweeted 43 times. Phase 4 of the PSBB and phase 1 of the Transitional PSBB experienced a surge in negative sentiment. Several things caused this. News about the distribution of 672 new cases of COVID-19 in Indonesia DKI Jakarta was the highest with 11 retweets and 29 likes.

To analyze surprise emotions for each phase in the Jakarta PSBB, the following is a graphic of surprise emotions depicted in figure 8.

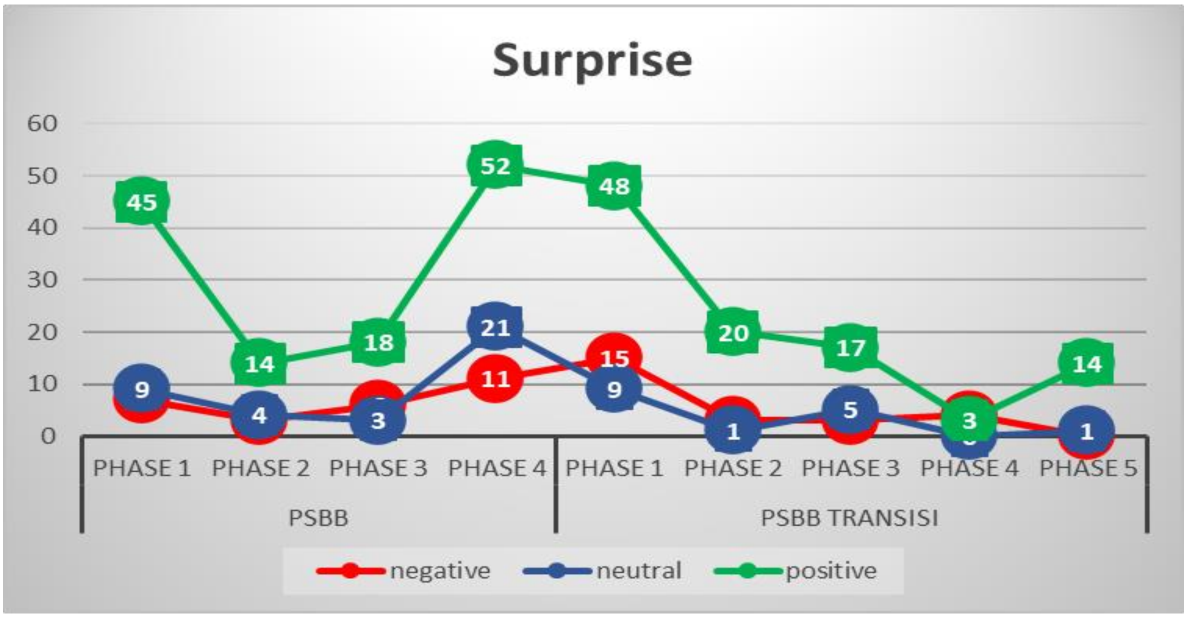

Figure 8: Emotional Surprise Graph

It can be seen in figure 8 that positive sentiment is higher than PSBB phase 1 to phase 4 to PSBB transition phase 1 to phase 4. In phase 4, Transitional PSBB experienced a decrease in positive sentiment due to the tweet "cool indeed the governor ane pak anies" retweeting 34 and likes by 91 other users. In phase 5 of the PSBB, the positive sentiment transition experienced an increase again due to similar tweets in phase 4 with 34 retweets and 88 Twitter users liked.

To analyze anger emotions for each phase in the Jakarta PSBB, the following is a graphic of anger emotions (figure 9).

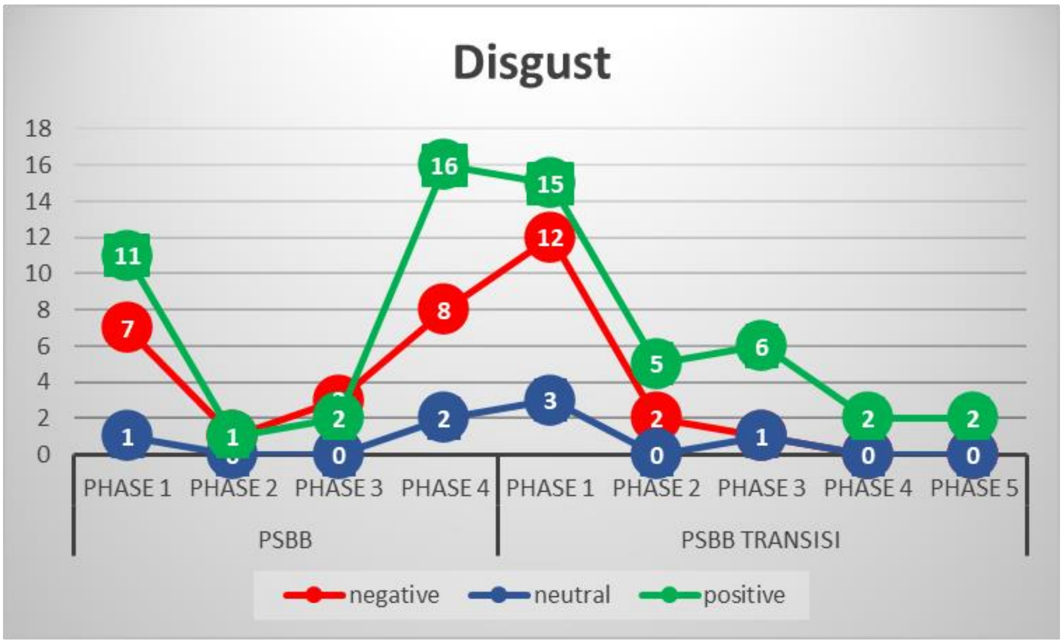

Figure 9: Emotional Happiness Graph

In figure 9, it can be seen that the highest positive sentiment was in phase 4 of the PSBB and experienced a decline in the Transitional PSBB. Tweets classified as emotions of disgust are the fewest in number because for dictionaries classified as emotions of disgust, the number is the least among other emotions. Phase 3 of the PSBB negative sentiment increased, making it the highest. This was due to the news that the coronavirus could emerge again at the end of 2020. After the news was reported, it immediately made negative sentiment rise.

In implementing the PSBB in Jakarta, public sentiment on Twitter can be an input for the government as one of the success factors in implementing policies. In table 2, it can be seen that the overall results of the sentiment on the implementation of the PSBB are based on emotional factors that the author has processed.

Table 2

Summarizes the number of sentiments of each type of emotion

No	Kind of Emotion	Code	Sentiment Class		
			Negative	Neutral	Positive
1	Happiness	[1]	776	1281	5246
2	Sadness	[2]	557	350	546
3	Anger	[3]	1221	697	1077
4	Fear	[4]	250	85	212
5	Surprise	[5]	52	53	231
6	Disgust	[6]	34	7	60

Table 2 shows the overall number of sentiments for each emotional factor. The data will then be illustrated through a bar chart that explains the *general* sentiment data. Figure 10 is a diagram depicting the overall results of the sentiment on the implementation of PSBB based on emotional factors.

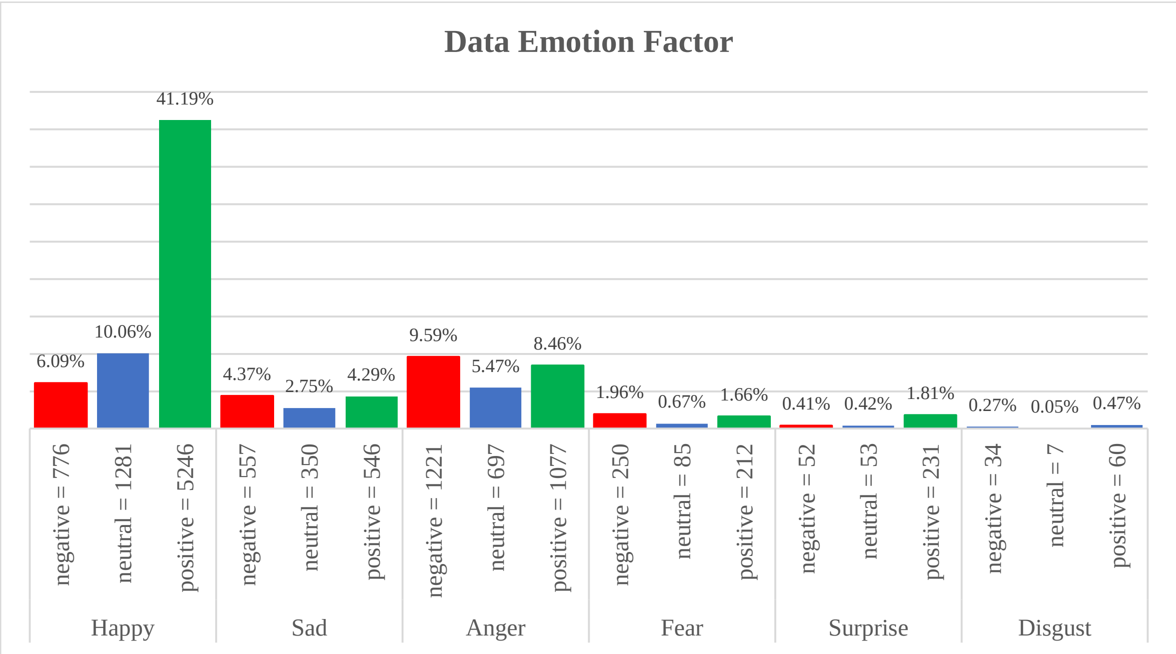

Figure 10: Emotions Sentiment Percentage Diagram

With the implementation of the PSBB in Jakarta, which has been in effect since *10 April*

2020, many people have expressed their emotions on social media *Twitter*. In figure 10, *it can be concluded that the emotional happiness factor has the highest positive sentiment (41.19%), where* emotional happiness is an expression characterized by feelings of satisfaction, joy, *and prosperity. The application of the Jakarta PSBB for the emotional happiness of the community is on a positive measure. Then for neutral sentiment in second place and negative sentiment at the lowest position.*

Discussion

The emotional state of social media users is easily influenced or manipulated by the content on social media itself. Content or writing that is written emotionally can trigger the same emotions for readers. When a social media user, such as Twitter, sees a friend *was writing something that contains happy emotions, readers of the article can immediately feel the happy emotion. This can* be *dangerous if the information or writing shared on Twitter triggers divisions and is not guaranteed the truth or is commonly known as a hoax* (Ferrara & Yang, 2015).

With the outbreak of COVID-19 in Indonesia, several regions such as Jakarta have responded quickly. *The PSBB has been implemented in Jakarta from 10 April* 2020 to *22 January* 2021. *All people in Jakarta must obey this PSBB policy to reduce the transmission of COVID-19. In every policy implemented, the govern*ment *expects a positive response or support from the community.*

From analyzing people's emotions on Twitter, people's emotions are happy, with the highest positive sentiment of 5246 towards implementing the PSBB in Jakarta. However, this result is different from the number spread in Jakarta as of 9 November 2020, amounting to 112,027, 25.6% of the total number of confirmed positives in Indonesia. With the spread as of 9 November 2019 totaling 716 confirmed positives, the number has decreased from the previous three days from 1,118 on 7 November and 826 on 8 November. Jakarta ranks the highest in Indonesia with positive confirmed numbers (Gugus Tugas Percepatan Penanganan COVID-19, 2020).

Evaluation

Table 3 shows the results of the accuracy comparison between the SentiStrength method and the Support Vector Machine method.

Table 3
Evaluation method

Method	Accuracy	Precision	Recall	F-measure
Sentistrength	88,33%	86,67%	89,66%	88,14%
SVM	73,33%	68,57%	82,76%	75,00%

In table 3, *several variables can be compared, which states the method's accuracy. This study uses the* SentiStrength method because after being compared with the SVM method, it turns out that the SentiStrength method is superior in all variables used, *such as accuracy, precision, recall, specificity, and f-measure. With these* considerations, the writer finally uses the Sentistength method in this study.

Conclusion

From the research that has been carried out on the implementation of the Large-Scale Social Restrictions policy in DKI Jakarta, it can be concluded that in the application of the DKI Jakarta Large-Scale Social Restrictions policy from *10 April* 2020 to *22 August* 2020, the public on *Twitter* tends to be happy with the implementation of the PSBB. Overall, positive sentiment on happy emotions made 5246 tweets with 41.19% and was the highest sentiment in implementing the PSBB policy. *Implementing the PSBB in DKI Jakarta raises happy emotions from the community, so further implementation needs to be evaluated with attention to the community's emotions.*

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