Sentiment Analysis as Assessment of the COVID-19 Social Assistance Pollemic using Random Forest Algorithm

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***Abstract*—The government's endeavors in organizing the COVID-19 Social Assistance program often encounter problems and lead to the opinion of many parties. One of the opinions expressed on social media is twitter. Sentiments from these opinions were then analyzed to find out the assessment and discussion of each sentiment that can be used as evaluation material for the Social Assistance program. In this study, the sentiment of each preprocessed text was obtained using a labeling process with an assessment of polarity and subjectivity from TextBlob library. The results of neutral, positive, and negative sentiment assessments were weighted using TFIDF. Words that have been formatted into numeric then classified using the Random Forest algorithm. The parameters in this case were in accordance with the documentation on sklearn. An evaluation of the algorithm was also carried out using the 10 kfold cross validation method as a performance validation of the results of testing each piece of data. The performance obtained is quite satisfactory.**

Keywords— sentiment analysis, bansos, random forest, twitter, polarity, subjectivity, tfidf

I. INTRODUCTION

COVID-19 Social Assistance is a form of state responsibility to affected communities to at least anticipate socio-economic problems related to COVID-19. However, the distribution of social assistance has too many and not harmonious regulations from the government. The social assistance provided seemed confusing, the acceptance time was quite long, and it was received by the community less well on target [1]. The problem was later revealed and had been widely discussed on social media since December 2020 which discussed the COVID-19 Social Assistance corruption case [2]. Then government pursue to make improvements, such as distribution acceleration, data improvement, and allocation method. One of the things that is being strived for is the acceleration of distribution before the Eid al-Fitr 1432 H [3].

During the span of five months from December 2020, the government pursued its efforts to distribute social assistance. There were various responses from the public, for example the trending #BangkitnyaKKN on January 25, 2021 which brought back the issue of aid corruption[4]. From these responses, various kinds of information can be obtained.

One of many ways people express opinions is via Twitter. Recent reports from We Are Social and Hootsuite in January 2021 show the potential information gathering from Twitter. It is reported that Twitter is one of the social media in Indonesia that has the most active users (63.6%) every month, with an age range of 16-64 years. In this age range a person is considered an adult and has the ability to observe and respond to issues that are happening [5]. The breadth of data from Twitter can also support the accuracy of the algorithm to be used.

Opinion extraction from twitter requires precision to produce accuracy. Due to results of twitter data mining have an untidy structure and are often written in a language that is not up to standard. The method to classify opinions is sentiment analysis [6]. In previous research, sentiment analysis regarding the discourse of moving the Indonesian capital city succeeded in providing the percentage of the results of the pros and cons of public responses. The number of pros who are the majority in this study can be considered because the data is directly from the comments of the public when the issue had become a trending topic. In other words, the public's response to a policy is important for the government to make decisions. The results of this sentiment analysis take the types of words with the majority of verbs and adjectives[7]. Likewise, the sentiment analysis research carried out raised the issue of social assistance with the relationship between the verbs of the government's efforts to overcome the problem, and adjectives that became the link in determining sentiment. In addition, this research takes a moment when the issue of social assistance is hotly discussed. The way people express opinions is via Twitter.

An algorithm is needed to classify opinions. Sentiment classification will be carried out using Random Forest. Previous research has shown that Random Forest is a good algorithm for multi-class classification. Multi-class sentiments with conditional statements identified by adding

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some aspects to the data. More extensive data is needed in the implementation of the Random Forest[8]. This is because the splitting when creating a tree does not identify all variables, only selects some variables to get the best results from the large amount of data. When checking for fewer variables, the correlation of each tree will tend to be smaller. This small correlation will improve the performance results of sentiment classification [9].

High performance indicates that the classification and inference of data into information can be done well. In the previous sentiment analysis research, the evaluation of model classification performance was successfully carried out by measuring accuracy, precision, recall and f1-score. With this performance, an analysis of the error type is obtained from the comparison between the results of the classification algorithm and the actual classification [10].

Each processed data requires a good management method. CRISP-DM is a method to extract data into knowledge. Based on many surveys and polls, standard for data mining development is the CRISP-DM method [11]. CRISP-DM in the social science domain increase productivity in terms of time and research quality. Complex knowledge extraction produces unique characteristics [12]. The domain is related to the domain of this research, that is social science and economics.

II. METHODOLOGY

The methodology is adapted to the following flow of CRISP-DM development methods:

1) *Business Understanding,* analyzing the problem starting from observing the phenomenon to determine business goals, reviewing resources, determining the goals and success of data collection, and project planning.
2) *Data Understanding*, collects all data that has been taken, details of data such as data type, amount of data, variables in each column, and so on. The data is then visualized to see the level of cleanliness of the data.
3) *Data Preparing*, selecting data to be used and not, cleaning data by correcting, associating or deleting incorrect or unneeded values, constructing data by assigning new attributes (labeling), formatting by converting strings to numeric.
4) *Modeling*, analyzing how the overall algorithm works on the data, design the data set into training data and test data, then build the algorithm
5) *Evaluation,* evaluating algorithm performance, sentiment percentage, and topic of sentiment analysis results.

III. RESULT AND DISCUSSION

A. Business Understanding

Problem analysis from observing phenomena shows that hashtags discussing the topic of COVID-19 Social Assistance have several times become trending topics in Indonesia, such as #TangkapanakPakLurah [13], #madambansos [14], and #BangkitnyaKKN [4]. Moreover, the @KemensosRI account continues to publish its handling efforts through Twitter social media. The explanation shows the potential information from twitter data [15].

One of the distribution efforts made is the acceleration of distribution before Eid [3]. Data retrieval is considered successful when tweet data is obtained from the period 5-12 May 2021 which coincides with that moment. Researchers want to know whether the efforts made are sufficiently discussed or not, and of course know the majority of the sentiments of the opinions.

The type of sentiment analysis is Aspect Based Sentiment Analysis by conducting automatic opinion assessments using the TextBlob library. There are three types of values, that is neutral, positive, and negative. This determination is in accordance with the purpose of sentiment analysis, which is to assess opinions regarding the COVID-19 Social Assistance.

B. Data Understanding

After collecting data for sixteen days, the amount of data is 45,608 “Fig.1”. From these details, visualization is obtained by using the matplotlib library in python “Fig.2”, “Fig.3”, and “Fig.4”. “Fig.2” shows hashtag trends as an approximate range of the most discussed topics. It can be seen twitter users did not explicitly talk about efforts to accelerate the distribution of social assistance that was reported during the data collection period, but the hashtag still indicated the topic of social assistance which would be very helpful in discussing the results of sentiment analysis in the word cloud.

“Fig.3” shows that the most common source of tweet writing is Twitter for Android. This source shows that many opinions are written directly by the public. From the data from December 2019 to December 2020, Android users in Indonesia got the first position with a percentage reaching 92.3% of the total operating system surfing the internet [5]. Where the topic of sentiment analysis is to evaluate the opinion of the majority of the community. Further information about user data can be seen in “Fig.4”. This is data that proves that the majority of tweets come from the public. These users are active in voicing their opinion about social assistance.

```
RangeIndex: 45608 entries, 0 to 45607
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Tanggal         45608 non-null  object
 1   Tweets          45608 non-null  object
 2   ID              45608 non-null  int64
 3   Screen Name     45608 non-null  object
 4   Banyak Retweet  45608 non-null  int64
 5   Source          45608 non-null  object
 6   Retweet Status  45608 non-null  int64
 7   Hashtags        45608 non-null  object
dtypes: int64(3), object(5)
memory usage: 2.8+ MB
```

Fig. 1 Tweet Data Attribute Details

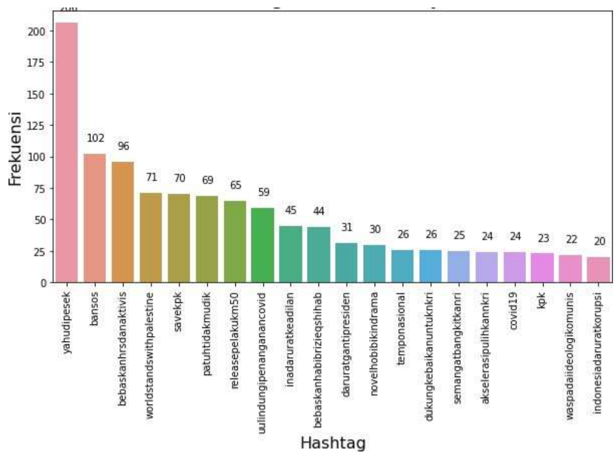

Fig. 2. Trending Hashtags

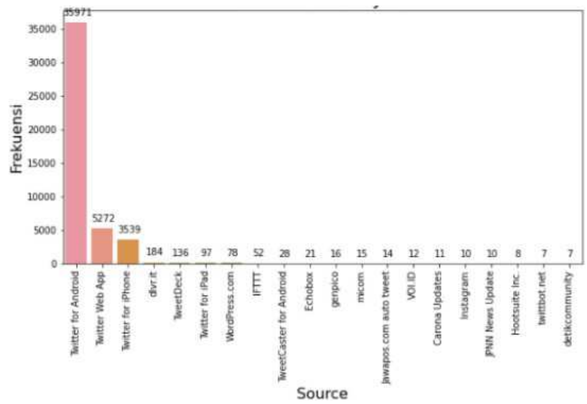

Fig. 3. Most Source

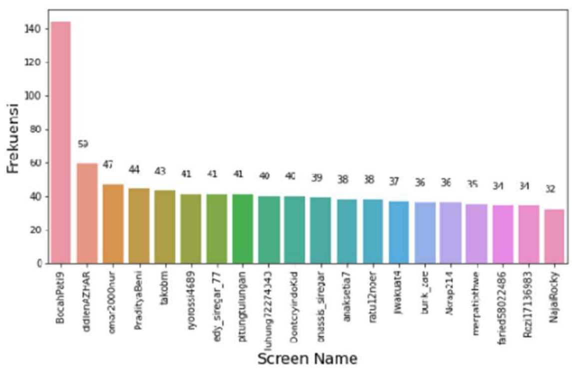

Fig. 4. Most User

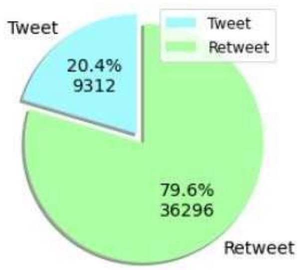

Fig. 5. Comparison of Tweets and Retweets

"Fig."5 shows how clean the quality of the data is. From the amount of data, the original/clean tweets ranged from 20.4%. Data shows the number of tweets from those who actually have an opinion. Although the number of retweets is quite large, the expression of this retweet is ambiguous. Those who share tweets can have positive sentiments such as supporting, neutral or just sharing, and negative expressions such as disapproving.

C. Data Preparing

From the explanation of tweet and retweet data, it can be concluded that the selected data is only tweets. In addition to being ambiguous, many values from the retweet data are repeated with the same content, so the retweet content is also deleted in the retweet comment. In other words, the type of tweet is taken from the comments only.

The data that has been selected is then cleaned by several methods. Methods are case folding, data cleaning, tokenizing, stop words removal, stemming, and remove punctuation. An example of the results of text cleaning attached in Table I.

TABLE I. SAMPLE CLEANING RESULT

Raw data	b'Awas Hoaks Pendaftaran Penerima Dana Bansos Tahun 2021! https://t.co/Ao6Ri7Z7Hl'
Case folding	b'awas hoaks pendaftaran penerima dana bansos tahun 2021! https://t.co/ao6ri7z7hl'
Data Cleaning	awas hoaks pendaftaran penerima dana bansos tahun 2021
Tokenizing	awas, hoaks, pendaftaran, penerima, dana, bansos, tahun, 2021
Stop words Removal	awas, hoaks, pendaftaran, penerima, dana, bansos, 2021
Stemming	awas, hoaks, daftar, terima, dana, bansos,2021
Remove Punctuation	awas hoaks daftar terima dana bansos 2021

Furthermore, the accumulated assessment using polarity and subjectivity can be seen in "Fig.6". The average value of subjectivity labeling as a whole gets 0.213283. Then the positive label is 0.20955, and 0.4303 for the negative label.

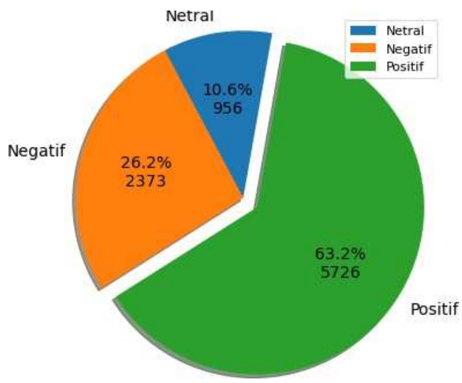

Fig. 6. Percentage of Sentiment Labeling

Data then goes through a formatting process to be understood by the machine. TF-IDF method results in changing terms from text to numeric. Example calculation formatting can be seen from the text data below and Table II:

W = *cek bansos 2021*

X = *jujur indonesia susah atur patuh atur bagi bansos sedih*

Y = *setan minder buy korup asuransi bansos*

Z = *cek terima bansos kemensos cair mei login viacom nasional*

TABLE II. TF-IDF Weighting Calculation

Term	TF						IDF $= log\ (\frac{D}{df})$	$W_{dt}=TF_{dt}*IDF_{ft}$			
	W	X	Y	Z	df	$\frac{D}{df}$		W	X	Y	Z
2021	1	0	0	0	1	4	0,602	0,602	0	0	0
asuransi	0	0	1	0	1	4	0,602	0	0	0,602	0
atur	0	2	0	0	2	2	0,301	0	0,301	0	0
bagi	0	1	0	0	1	4	0,602	0	0,602	0	0
bansos	1	1	1	1	4	1	0	0	0	0	0
buy	0	0	1	0	1	4	0,602	0	0	0,602	0
cair	0	0	0	1	1	4	0,602	0	0	0	0,602
cek	1	0	0	1	2	2	0,301	0,301	0	0	0,301
Term	TF						IDF $= log\ (\frac{D}{df})$	$W_{dt}=TF_{dt}*IDF_{ft}$			
	W	X	Y	Z	df	$\frac{D}{df}$		W	X	Y	Z
com	0	0	0	1	1	4	0,602	0	0	0	0,602
indonesia	0	1	0	0	1	4	0,602	0	0,602	0	0
jujur	0	1	0	0	1	4	0,602	0	0,602	0	0
kemensos	0	0	0	1	1	4	0,602	0	0	0	0,602
korup	0	0	1	0	1	4	0,602	0	0	0,602	0
login	0	0	0	1	1	4	0,602	0	0	0	0,602
mei	0	0	0	1	1	4	0,602	0	0	0	0,602
minder	0	0	1	0	1	4	0,602	0	0	0,602	0
nasional	0	0	0	1	1	4	0,602	0	0	0	0,602
patuh	0	1	0	0	1	4	0,602	0	0,602	0	0
sedih	0	1	0	0	1	4	0,602	0	0,602	0	0
setan	0	0	1	0	1	4	0,602	0	0	0,602	0
susah	0	1	0	0	1	4	0,602	0	0,602	0	0
terima	0	0	0	1	1	4	0,602	0	0	0	0,602
via	0	0	0	1	1	4	0,602	0	0	0	0,602

D. Modelling

Random Forest modeling technique providing a simple sample by first changing data type of predicted value into categories and tweet data into strings. As a development algorithm from Decision tree, Random Forest has a difference in the number of trees generated. The tree results from this algorithm have more numbers. From the default of sklearn parameter, Random Forest produces a total of 100 trees. In the ensemble technique, predictions are combined from several basic estimators built by the decision tree to increase the robustness of the independent estimator data. In determining the terminal and splitting nodes, Gini calculations are used with reference to the right and left data propositions. When the calculation of the result that appears is equal to 0, the node will stop splitting. Otherwise, splitting will continue. In doing splitting, the number of features in each tree can be determined.

The resulting collection of trees is used as a vote to determine sentiment. The tree is supported from training data and independent random features with different features. When you want to classify new data, the resulting tree gives one vote.

Modeling implementation started when training data and testing data have been determined. In this study, the separation was carried out using cross-validation evaluation which divided data into 10 folds. Machine then calculates the number of each word or feature from the testing data contained in training data. Calculations are separated between words labeled as neutral, negative, and positive, then the sum of two is added to then calculate Gini (gini = 1 - $(pi)2$). Each Gini recalculate value of Gini impurity to determine top node or splitting next branch until it is complete. Only then did Random Forest vote to determine the label for each tweet.

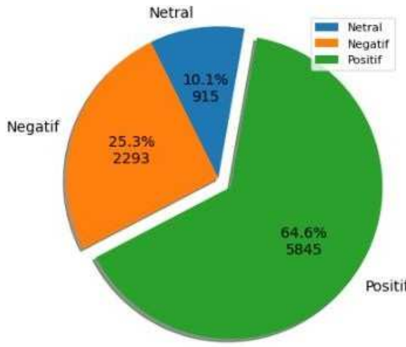

Fig. 7. Sentiment Percentage After Classification

Fig. 8. Positive Word Cloud

Fig. 9. Negative Word Cloud

Fig. 10. Neutral Word Cloud

The results of the build model are predictions of the Random Forest and word cloud classification as the result of the discussion topic “Fig. 8.”, “Fig. 9.”, “Fig. 10.”. From

"Fig.7." positive sentiment gets an additional percentage of about one percent from the labeling done "Fig.6". Where the algorithm reads other sentiment groups which should be positive. From the figure, it was found that the machine detecting the topic of social assistance received a positive rating.

E. Evaluation

a) Sentiment Percentage: Results of the Random Forest classification "Fig.7." show that the majority of opinions are positive sentiments. If we look back at the process of business understanding and data understanding "Fig.2", this topic has quite an interesting discussion on corruption cases which actually have a negative sentiment. The process that affects the data obtained is labeling using polarity calculations. Polarity gives the value of a word according to its true meaning. Meanwhile, Twitter frees users to express their opinion according to their style. Like the word '*duta*' "Fig.8" which actually refers to the public's sarcasm about the social assistance ambassador. After re-reading the tweet, the word was widely discussed because of the controversial appointment of ambassadors, then the public was concerned with the topic of social assistance. An example of a tweet containing the word ambassador is "*'b'yang korupsi bansos ga sekalian jadi duta bansos?''*. Even after being classified, the word remains in positive sentiment because the voting process shows that the majority of the word is found in positive words. This statement is supported by a positive subjectivity value of only around 20%. In other words, the machine detects that the opinions expressed are close to the facts, or naturally include objective. The subjectivity value on negative sentiment shows that about 40% of the text is subjective. This number means that the negative value of a text is not very objective. One of the explanations of this situation is due to the data cleaning process. The conversion of words into basic words using a *sastrawi* library is still not completely perfect. There are words that are detected to have prefixes, suffixes, or confixes when in fact they do not. Likewise with the stopwords removal process, it is necessary to re-check the deletion of every word that is considered lacking or has no meaning. That way, machine errors in judging can be reduced. If look back at the TextBlob documentation, the labeling function using the polarity method is only available in English. There is the possibility of errors in the translation process that can change the meaning of a sentence. The thing to remember is not everyone can judge an opinion that is conveyed. It takes a linguist to interpret it. On the other hand, the labeling method using polarity makes it very easy to understand a sentence. In addition, the Random Forest algorithm will vote for the most number of votes. When a word is found in other sentiment words as well, the model will predict that word as the most sentimental word.

b) Sentiment Analysis Topic: Sentiment Analysis Topic Positive sentimental words "Fig.8" show the words '*fitur*', '*urus*', '*duta'*, and '*kawan*' as words that often appear. There is an interesting word to discuss, the word 'fitur' refers to a government program making efforts to create an application for monitoring the distribution of social assistance. One of the purposes of monitoring is to avoid duplicate data and fake vendors or companies. Continuing with '*bansosjaga*' and '*linjamsos*' which discuss the protection for those involved in the distribution of social assistance. The negative word cloud "Fig.9" displays the words *'miskin'* and *'cilik'* as the most talked about words. Basically, both words are really negative sentiments. The machine successfully detects words that are actually negative. The word '*miskin*' is not very specific in referring to the discussion on the topic of social assistance. But basically, social assistance is synonymous with poverty and the poor people who receive it. The word *'cilik'* is a negative call or greeting to those who are considered incorrect in tackling or distributing social assistance funds. The word is related to the most popular hashtags that talk about corruption. It is also supported by the emergence of the word *'korup'*. From this negative wordcloud, the word '*rp74*' is also seen which refers to the case of the government overpaying vendors for the distribution of social assistance of Rp.74 billion. In the neutral world cloud "Fig.10", there is the same word as the positive word cloud, namely *'kawan'*. This shows that words contained in neutral sentiments have a high chance of being found in other sentiments. The next discussion is the word 'world'. In "Fig.2" #worldstandswithpalestine got the 4th position as the most discussed topic. So the word 'world' is related to the topic. Although the word is not included in the topic of social assistance, on social media Twitter there is a habit to enliven important or interesting issues. So, the sentence containing 'world' still contains a discussion about social assistance. This also shows that this topic is important to be discussed according to the community.

c) Random Forest Performance: Of the total 12,976 features, Random Forest bootstrapped 100 trees with each tree having a feature according to the root value of the total number of features obtained. The experiment resulted in various kinds of trees which definitely have uncorelatedness properties. Coupled with the weighing of three sentiment decisions, it produces branches that have a variety of decisions on each feature. The performance of Random Forest with sklearn parameter in this study resulted from the evaluation of 10 k-fold cross validation because it has been tested experimentally in producing a model with a lower level of bias [16].

TABLE III. RANDOM FOREST ACCURACY AND PRECISION TEST RESULTS

K	Acc	Precison%		
	%	0	1	2
1	75	52	87	76
2	75	55	83	74
3	73	48	74	75
4	78	56	83	80
5	76	59	83	77
6	81	45	91	78
7	78	63	78	80
8	70	61	83	70
9	76	57	77	78
10	78	62	78	79
Avg	76	55,8	81,7	76,7
		71,4		

TABLE IV. RANDOM FOREST RECALL TEST RESULTS AND F1-SCORE

K	Recall %			F1-score%		
	0	1	2	0	1	2
1	52	42	93	52	57	84

2	28	43	94	37	56	83
3	31	41	92	38	53	83
4	56	47	92	56	60	86
5	44	55	92	51	66	83
6	21	78	92	28	84	84
7	39	51	93	48	62	86
8	60	41	87	61	55	78
9	42	43	92	49	55	84
10	36	49	94	45	60	86
Avg	40,9	49	92,1	46,5	60,8	83,7
	60,67			63,67		

The discussion of Random Forest's performance begins with the accuracy value which can be seen in the TABLE III. (76%). This means Random Forest model is quite good at classifying text. The factor that causes the accuracy value is not maximized is the false value which generated. In Random Forest, the voting process is a way to determine a classification. Each tree predicts each word with a different label, then the majority label is taken to determine the results of text classification. This explanation is behind the occurrence of false in the model. For example, the word "*korupsi*" gets a negative classification result, it's just that the word is also found on a positive label. Then the positive label will detect the occurrence of false negatives. The next discussion is the precision performance which shows the model's ability to re-classify according to the labeling that has been done TABLE III. Precision performance got an average value of 71.4%. The highest precision value is found in negative sentiment. It can be concluded model can detect negative words well in the text. Where the comparison between true negative and false negative is not too significant. The recall value TABLE IV only reached 60.67%. In the recall calculation, false number is very influential to determine the performance of the model in returning information for a word. In the cases found, the false comparison between the three sentiments is quite high with the highest value on label 2 (positive) while the other false has a fairly small value. Therefore, the best recall performance is found on the positive label. The false value obtained is influenced by the number of words contained in the label. In this situation, false can occur because the word in one sentiment is in another sentiment. The model's performance on the f1-score shows a value of 63.67%. With the lowest number obtained neutral sentiment. Neutral sentiment has a fairly small number because the words contained in this label are found in many other labels. Where the value of polarity in the labeling process considers the influence of the adjective and the level of quality. While neutral sentences usually have a weight with most nouns or values between adjectives having a balanced value. Things that can be considered to reduce the value of false is by voting from a larger number of trees. This will increase the variety of a tree and can ensure a word is on the label it should be. However, the addition of the tree must consider the value of uncorrelatedness. This value aims to ensure that the type of tree created does not have a model that is too similar between one tree and another. For example, limiting the number of leaf nodes on each tree. That way, the number of trees will be divided into several types to validate the decision at the final voting. Without considering uncorrelatedness, then the performance values tested will not differ much from the research that has been done.

IV. CONCLUSION

This study gives the results of the percentage of positive sentiment as the highest value "Fig.7". In other words, the machine assesses the social assistance program is rated or responded positively by twitter users. It's just that these data have shortcomings in detecting sarcasm sentences through polarity assessment. It can be interpreted, the assessment obtained is not completely positive according to the percentage. The cause of this situation is the lack of a data cleaning process and a translation process that allows changing the meaning of a sentence. So that there is an error in the assessment of polarity and subjectivity.

Even though it has various shortcomings, the sentiment percentage results can produce the main topic according to each tendency. The data understanding stage in the CRISP-DM method is very helpful in concluding the topic from the resulting word cloud. From "Fig.8", it shows that the positive topic did not discuss the acceleration efforts that were reported during the data collection period. Even so, there is a discussion about good countermeasures from the government, namely features for monitoring the distribution of social assistance. Then in the negative word cloud "Fig.9" the results show the nicknames that are often used in cases of corruption in social assistance. In addition, negative word clouds can display problems that are the main conversation. The neutral word cloud "Fig.10" can show there is urgency to discuss this topic.

The performance of the classification algorithm can be said quite satisfactory. The accuracy value indicates that Random Forest has succeeded in classifying. Likewise with precision performance, which can detect words with negative sentiments well. However, Random Forest's ability to restore value or recall is not good enough. On the f1-score itself, the weighting of precision and recall abilities obtained similar results. Due to the number of false positive sentiments has more than other sentiments. Where the false value affects the calculation of recall performance and f1-score.

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