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Sentiment analysis of community response Indonesia against covid-19 on twitter based on negation handling

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Abstract

Tracking and analyzing tweets can be a method to find out people's thoughts, behavior, and reactions regarding the impact of Covid-19. The key to sentiment analysis is the determination of polarity, which determines whether the sentiment is positive or negative. The aim of this research is to obtain optimal sentiment analysis performance from the implementation of Negation Handling on sentiment analysis of the Indonesian people's response to the impact of COVID-19 on Twitter. This research uses Sastrawi for the stemming process of Twitter posts, then through the character cleansing process, the combination of n-grams and Multinomial Naive Bayes is used for the classification stage. In addition to this, this study also uses 3-fold cross-validation, and evaluation using the Mathew Coefficient Correlation (MCC) to see the performance of adding Negation Handling to the classification algorithm. The addition of negation is by giving the label "_neg" to a document if a negation word is found such as "tidak, bukan, belum, jangan" before the punctuation mark on a document. In this study, the accuracy obtained was 59.6% compared to adding negation handling, the accuracy obtained was 59.1%. Although the percentage result is not high, documents that include negative sentences have more meaning as negative sentences.

1. Introduction

COVID-19 is a disease that was originally known as Coronavirus disease 2019 which was declared a pandemic by the World Health Organization (WHO) on March 11, 2020 [1]. The impact of *COVID-19* has now become a source of depression, stress, and anxiety that can lead to mental illness for someone, which can be due to the large amount of misleading information posted on social media [2]. Mental health can also be affected by the rapid spread of false information on social media [3]. We can take the information from the community's response to the impact of *COVID-19* to find out how the current condition of the community is and can also be used as decision making, such as improving the handling of people who are mentally and economically affected by *COVID-19* [4]. This information retrieval process can be done by utilizing text processing or text analysis, namely Sentiment Analysis [5].

Sentiment analysis is a process used to describe sentiments or opinions expressed by someone on a particular topic [6]. To carry out the identification process and subjectively process information obtained from data sources. The process of Sentiment Analysis is assisted by using a scientific approach called Natural Language Processing (NLP) which studies the internal structure of humans, namely neurological processes or language and patterns of human behavior [5]. Tracking and analyzing tweets can be a method to find out people's thoughts, behavior, and reactions regarding the Covid-19 problem [6].

The key to sentiment analysis is the determination of polarity, which determines whether the sentiment is positive or negative [7]. The problem is in any sentiment analysis case the word negation in a sentence can change the polarity of the sentence [8]. So, that if it is not handled properly it will affect the performance of the sentiment classification. Therefore, an effort is needed [9].

Machine learning has become a very powerful tool for classifying sentiments especially in the problem of handling negation. In previous studies regarding the analysis of the effect of Negation Handling in Indonesian using the First Sentiment Word (FSW) and Rest of Sentence (ROS) and Fixed Window Length (FWL) algorithms with n = 1-5 able to increase the accuracy rate of 2.43%, the precision of 2.38%, and recall of 2.93% [10]. Another researcher from R. Amalia et al, who also added Negation Handling for sentiment classification on Indonesian Twitter by using rule based, was able to improve the performance of the classification, namely the average value of F1 increased by 5% than without negation handling [11]. Although the accuracy obtained may not be optimal, Negation Handling can affect the meaning of a sentence.

In this paper the author using the twitter dataset as training and test data, this study produces sentiment analysis using Sastrawi for the stemming process of twitter writing, then through the character cleansing process, the combination of n-grams and Multinomial Naive Bayes is used as a learning model. In addition to this, this study also uses 3 fold cross validation, and evaluation uses the Mathew Coefficient Correlation (MCC) to see the performance of adding Negation Handling to the classification algorithm. In contrast to previous studies, in this study the handling of negation is by giving the label "_neg" to a document if a negation word is found such as "*tidak, bukan, belum, jangan*" before the punctuation mark on a document.

2. Research Method

In this study, sentiment data from the public's response to *Covid-19* on Twitter already has sentiment labels, namely positive, negative, which is then preprocessed by adding Negation Handling. Researchers took data from https://github.com/yahdiindrawan/covid19-sentiment-dataset. The total number of tweets taken was 905 Indonesian-language tweets with general aspects raised by the public about *Covid-19* in Indonesia on Twitter. Several stages to be carried out in this research are depicted in Figure 1.

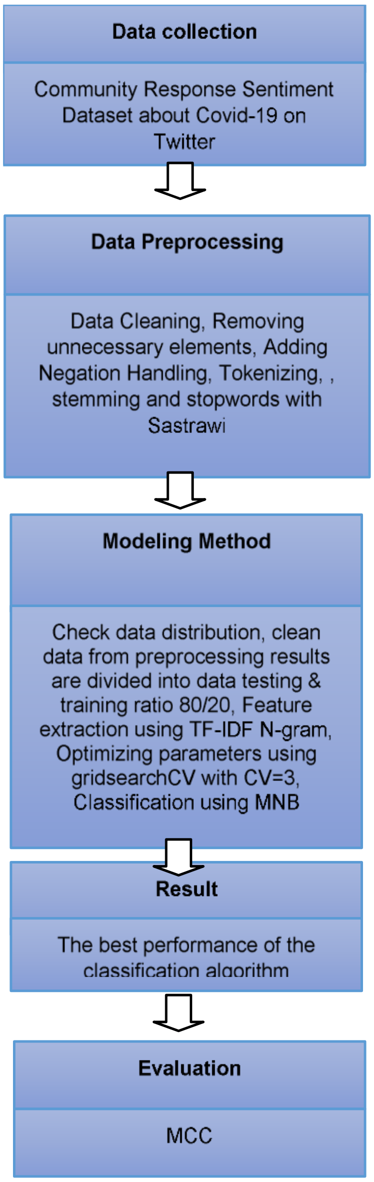

Figure 1. The Research Process

In this study, the author uses public data, namely the sentiment dataset of the Indonesian people's response to COVID-19 on Twitter. The dataset is a public dataset taken from GitHub by Yahdi Irawan's account (https://github.com/yahdiindrawan/covid19-sentiment-dataset) [12]. The data is unstructured data so the authors do pre-ppre-processhat the dataset turns into structured data which will later be processed in the proposed model. Sentiment dataset is taken as many as 902 data records that have a positive class of 441, negative 195, and neutral 266 data.

Preprocessing stages contained in this study are data cleaning, handling of negation, tokenization, stopword, stemming. Data cleaning is done to remove or clean some elements in the dataset to reduce bad errors and unnecessary elements in the data. The presence of unnecessary elements such as punctuation, etc., can affect the intrinsic characteristics during the classification process. The negation handler has the automatic nature of defining the scope as well as reversing the polarity of the word affected by the negation. In simple sentences (sentences containing one clause), usually a negation can reverse the polarity of all the words in a sentence [13]. However in, compound sentences (many clauses) a negation usually reverses the polarity of some words in the sentence and the number of words [14] ll be reversed varies according to the linguistic features [15]. In this study, the text weighting used is TFIDF and the N-gram feature.

Feature extraction is one of the important roles in the text classification process, which can be said to directly affect the text classification process[16]. In each word dimension is a dot that represents a feature (digital) of the text [17]. The text feature usually uses several sets of keywords[9]. After that, from the predetermined keywords, then the weight of each word in the text is calculated with a certain method which is then formed into a digital vector which is a feature vector of a text [18].

In this research, the writer uses the Multinomial Naive Bayes classification algorithm because MNB is used for text mining, and the dataset used is text data with a normal distribution. During the classification process, the data is divided into testing data and training data with a ratio of 80/20. The classification was carried out twice experiment to compare the results of the classification of two classes and three classes, namely the first classification of positive and negative classes, then compared with positive, negative, and neutral classes. Classification using the multinomial nave Bayes (MNB) algorithm using MNB model alpha parameters starting (0, 1, 0.01, 0.001), gridCV with cv = 3, and n-gram parameters, namely (1, 1), (1, 2) , (1, 3), (1, 4) by testing the two proposed models (added negation) and compared to the dataset without adding negation [19]. Multinomial Naive Bayes (MNB) is an algorithm that can classify a set of texts and documents. This algorithm is a developed version of the Naive Bayes algorithm [20]. The model generated by MNB is the result of calculating the frequency of occurrence of each word in a document. An example is if there is a set of class c and document d. So to calculate the probability of document d belonging to class c, we can use the Equation 1 [21].

$$P(d|c)\alpha\, P(c) \prod_{i=1}^{length(d)} P(\mathcal{W}_i|c) \tag{1}$$

where:
$P(d|c)$: is the probability of document d in document c
$P(c)$: is the probability of class c
$P(\mathcal{W}_i|c)$: is the probability of word I in document c

To see the performance of the classifier using the MNB by using several parameters, namely accuracy, precision, recall, and F1-score using the evaluation matrix method to find out how much data has been successfully classified using the MNB algorithm [12]. The author carried out two evaluation methods, namely using an evaluation matrix using the Mathew Coefficient Correlation (MCC). Matrics Mathew Correlation Coefficient (MCC) can be defined in terms of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). Which Equation 2 is written in the form of [22].

$$MCC = \frac{TP\ x\ TN - FP\ x\ FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{2}$$

Keterangan:
FN = *False Negative*
TP = *True Possitive*
TN = *True Negative*
FP = *False Possitive*
MCC = *Matthew Correlation Coefficient*

The MCC matrix can be calculated using the confusion matrix [12]. The calculation of the MCC metric uses four quantities (TP, TN, FP, and FN), which provides a better summary of the performance of a classification algorithm [23]. MCC is not specified if any of the quantities TP + FN, TP + FP, TN + FP, or TN + FN is zero. MCC takes values on the interval [−1, 1], with 1 indicating agreement, -1 indicating disagreement, and 0 indicating a prediction that has no correlation with ground truth [24].

3. Results and Discussion

At this experimental stage, what was carried out was to train the proposed model with the community response dataset to Covid-19 on Twitter in Indonesian. In this study, the dataset used was 905 tweets which had a distribution of 441 positive class data, 266 negative class data, 195 tweets of neutral class data. Then the 905 tweets were divided into training data and testing data with a ratio of 80% for training data and 20% for testing data. This study uses a machine learning model with the MNB Algorithm. Then apply K-fold 3 validation in the testing process for the entire document data set so that it can measure the performance of the classifiers. For evaluation, the author uses a confusion matrix for binary classes and for multiclasses using MCC.

The author uses binary classes and multiclasses to see this the performance of the classifier using the MNB by using several parameters, namely accuracy, precision, recall and F1-score using the evaluation matrix method to find out how much data has been successfully classified using the MNB algorithm. In addition, in this study the authors conducted two evaluation trials, namely for binary and multiclass data. This is done to determine whether the proposed method is more suitable to be applied to binary or multiclass data. The author carried out two evaluation methods, namely using an evaluation matrix using the Mathew Coefficient Correlation (MCC). The result is that implementation of negation handling on this study has proven to be good enough to improve the performance of the classifier. The Accuracy of the implementation the negation handling on sentiment analysis of Indonesian people's opinions regarding COVID-19 on Twitter results obtained are 59.6% compared to adding negation handling accuracy obtained is 59.1%.

3.1 Classification using MNB

Classification in this study the author usess the multinomial nave Bayes (MNB) because the model of Multinomial Naive Bayes classification is used for text mining, and the dataset used in this study are text data with a normal distribution. In this study author compared the model in binary and multiclass data to find this model is to find out if this model is suitable for application to binary or multi-class datasets. The MNB model alpha parameters starting (0, 1, 0.01, 0.001), gridCV with cv = 3, and n-gram parameters, namely (1, 1), (1, 2), (1, 3), (1, 4) by testing the two proposed models (added negation) and compared to the dataset without adding negation.

Table 1. Binary Class Classification Results

Without Negation	
Accuracy	0.773438 / 77%
Parameter	N-gram Range (1, 2)
With Negation	
Accuracy	0.789062 / 79%
Parameter	N-gram Range (1, 2)

Table 2. Multi Class Classification Results

Without Negation	
Accuracy	0.59116 / 59%
Parameter	N-gram Range (1, 3)
With Negation	
Accuracy	0.596685 / 59,6%
Parameter	N-gram Range (1, 4)

In Table 1 and Table 2 it can be seen that the classification of the proposed model gets the best parameter results on the MNB model alpha 0.01 parameter and feature extraction from the combination (1, 4) unigram with ngram.

3.2 Analysis of the influence of Negation Handling on pre-processing

To carry out the testing process and analysis of the classification performance, the addition of negation handling is added during pre-processing. The addition of negation handling is done during the data cleaning process so that the data to be processed already has a sentence with a negative label so as not to change the polarity of the sentence in a document that can affect the results of classification performance.

The addition of negation aims to make a sentence in the document more meaningful in that the sentence is a negative sentence [25]. The addition of negation is by giving the label "_neg" to a document if a negation word is found such as "no, no, not yet, don't" before the punctuation mark on a document. The results of adding negation to a sentence in the document can be seen in Table 3 below.

Tabel 3. Analysis of Addition of Negation Handling

Doc	Doc Sebelum penambahan negasi	Doc Sesudah penambahan negasi
Doc1	*Covid belum nyampe prigen mbak hmm hoax*	*covid belum nyampe_neg prigen_neg mbak_neg hmm_neg hoax_neg*
Doc 2	*Hikmah di balik musibah covid-19, smg para pejabat pemerintahan sadar lbh mengedepankan kekayaan negara utk kesejahteraan rakyat Indonesia, bukan memperkaya diri sendiri, keluarga dan kepentingan golongan. Apalagi membela kepentingan WNA, yg jelas2 melukai kepentingan rakyat.*	*hikmah di balik musibah covid smg para pejabat pemerintahan sadar lbh mengedepankan kekayaan negara utk kesejahteraan rakyat indonesia bukan memperkaya_neg diri_neg sendiri_neg keluarga dan kepentingan golongan apalagi membela kepentingan wna yg jelas melukai kepentingan rakyat*
Doc 3	*Ya Allah kami memohon pada mu perkenankanlah doa doa kami kerana sesungguhnya engkaulah yang maha pengasih lagi maha penyayang...Ya Allah lindungilah kami dari penyakit berjangkit covid 19... Aamiin.. aamiin ya rabbal a'lamin..stay at home.. jangan keluar rumah*	*ya allah kami memohon pada mu perkenankanlah doa doa kami kerana sesungguhnya engkaulah yang maha pengasih lagi maha penyayang ya allah lindungilah kami dari penyakit berjangkit covid aamiin aamiin ya rabbal lamin stay at home jangan keluar_neg rumah_neg*
Doc 4	*pagi... kenapa ya di daerah sy (cipinang besar selatan) rt 7 rw 6 nya tdk prnh aware dgn warganya. Setiap ada bantuan tidak pernah transparansi & kejadian covid ini jg tidak ada tindakan semprot disinfektan, dbd jg banyak tp tidak ada fogging. Tp uang kas ttp jalan*	*pagi kenapa ya di daerah sy cipinang besar selatan rt rw nya tdk prnh aware dgn warganya setiap ada bantuan tidak pernah_neg transparansi_neg amp_neg kejadian_neg covid_neg ini_neg jg_neg tidak_neg ada_neg tindakan_neg semprot_neg disinfektan_neg dbd jg banyak tp tidak ada_neg fogging_neg tp uang kas ttp jalan*
Doc 5	*Ada 15 cara menyuruh Covid-19 segera pergi, Jaga kebersihan dan ketertiban. Bukankah Covid-19 telah mendidik kita agar selalu menjaga kebersihan badan, pakaian, barang dan lingkungan dengan rajin mandi, mencuci tangan, dan tidak sembarangan membuang sampah?*	*ada cara menyuruh covid segera pergi jaga kebersihan dan ketertiban bukankah covid telah mendidik kita agar selalu menjaga kebersihan badan pakaian barang dan lingkungan dengan rajin mandi mencuci tangan dan tidak sembarangan_neg membuang_neg sampah_neg*
Doc 6	*Kementerian Agama Provinsi Papua Barat, Azis Hegemur mengatakan, Umat Islam di Provinsi Papua Barat diimbau agar tidak menolak pemakaman jenazah pasien positif terjangkit Covid-19. OPM*	*kementerian agama provinsi papua barat azis hegemur mengatakan umat islam di provinsi papua barat diimbau agar tidak menolak_neg pemakaman_neg jenazah_neg pasien_neg positif_neg terjangkit_neg covid_neg _neg opm*
Doc 7	*Jangan mudik dong! Ancaman penyebaran COVID-19 yang lebih luas. - Tandatangani Petisi! via*	*jangan mudik_neg dong_neg ancaman penyebaran covid yang lebih luas tandatangani petisi via*
Doc 8	*Berita seperti ini tidak akan ditengok oleh Muflis DUNGU Kecuali berita HOAX macam kudeta MBS, 150 pangeran kena COVID-19 yg sumbernya sama dari kaum LIBERAL*	*berita seperti ini tidak akan_neg ditengok_neg oleh_neg muflis_neg dungu_neg kecuali_neg berita_neg hoax_neg macam_neg kudeta_neg mbs_neg pangeran kena covid yg sumbernya sama dari kaum liberal*
Doc 9	*JANGAN ADA DUSTA DIANTARA KITA: Kisah Pilu Dokter Menangani Pasien Yang Ternyata Positif Covid-19*	*jangan ada_neg dusta_neg diantara_neg kita_neg kisah_neg pilu_neg dokter_neg menangani_neg pasien_neg yang_neg ternyata_neg positif_neg covid_neg _neg*
Doc 10	*Saya kuatir test Covid-19 belum menyeluruh Tau2 nanti ada korban tergeletak mati suspek corona Ngeri*	*saya kuatir test covid belum menyeluruh_neg tau_neg nanti_neg ada_neg korban_neg tergeletak_neg mati_neg suspek_neg corona_neg ngeri_neg*

The scope of negation used in this study is the scope of negation in Indonesian, namely "*tidak, bukan, belum, jangan*". Table 3 is an example of several documents from the community response dataset regarding COVID-19 on Twitter in Indonesian which can be seen in the doc column before adding negation and in the doc column after adding negation. In the table in the document column after adding the negation, it can be seen in the document that after finding the word in the negation scope, it will be labeled with "_neg" so that the sentence has more meaning.

3.3 Testing Method

To see the performance of the classifier using the MNB by using several parameters, namely accuracy, precision, recall and F1-score using the evaluation matrix method to find out how much data has been successfully classified using the MNB algorithm. In addition, in this study the authors conducted two evaluation trials, namely for binary and multiclass data to find this model is to find out if this model is suitable for application to binary or multi-class datasets.

Table 4. Value of Binary Class Evaluation Matrix

Training Data MCC Percentage	Intrepretation
0,99534	Very Strong
0,99534	Very Strong
Testing Data MCC Percentage	
0,49637	Week
0,49637	Week

Table 5. Value of Multi Class Evaluation Matrix

Training Data MCC Percentage	Intrepretation
0,98406	Very Strong
0,98041	Very Strong
0,97799	Very Strong
Testing Data MCC Percentage	
0,23385	Negliable
0,2441	Negliable
0,41387	Weak

The Table 4 shows the result of an evaluation using MCC on data that has two classes or binary classes. The training evaluation data shows very strong interpretation results in each class, namely positive and negative. In addition, the results for testing data are fairly weak or the results are not too good.

The Tabel 5 shows the result of an evaluation using MCC on data that has three classes or multi classes. The training evaluation data shows very strong interpretation results in each class, namely positive, negative, and neutral with a numerical value smaller than the value in the binary class. In addition, the results for testing data are fairly weak or the results are not too good with a value smaller than the number results in data that has two classes or binary classes.

To see the performance of the classification algorithm, the authors compare the classification using a Decision Tree and K-Nearest Neighbour to see which classification algorithm has the best performance. The results of the accuracy of adding negation to the dataset with datasets that do not have additional negations can be seen in Table 6 and Table 7 below.

Table 6. Value of Binary Class Evaluation Matrix

Model	Training Accuracy	Test Accuracy
Naïve Bayes Multinomial	**0.998031**	**0.789062**
Decision Tree	**0.698819**	**0.671875**
K-Nearest Neighbour	**0.805118**	**0.742188**

Table 7. Value of Multi Class Evaluation Matrix

Model	Training Accuracy	Test Accuracy
Naïve Bayes Multinomial	**0.987517**	**0.596685**
Decision Tree	**0.712700**	**0.516484**
K-Nearest Neighbour	**0.712700**	**0.593407**

Table 6 and Table 7 show that the Multinomial Naïve Bayes algorithm, especially in the Binary Class dataset, has the best parameters for classification results. The result of dataset classification with negation handling is 0.98 for training data and 0.78 for testing data on Binary Class dataset. Meanwhile, for the Multiclass dataset with negation handling, the accuracy results are 0.98 for training data and 0.59 for testing data.

4. Conclusion

The implementation of negation handling on sentiment analysis of Indonesian people's opinions regarding COVID-19 on Twitter has proven to be good enough to improve the performance of the classifier. Accuracy results obtained are 59.6% compared to adding negation handling accuracy obtained is 59.1%. Although the percentage result is not high, documents that include negative sentences have more meaning as negative sentences. However, for the evaluation using the MCC evaluation matrix, the results were quite good for the testing data. For the results of the proposed method whether it is suitable for data that has two classes or three classes when viewed from the results of the evaluation matrix, the proposed method is more suitable for binary data or data that has only two classes. The results of the evaluation matrix for binary data have a larger number, namely 0.99534 on training data and 0.49637 on testing data. Although the accuracy obtained from the proposed method has not yet obtained maximum results, which is caused by imbalanced data that can affect the level of accuracy obtained, but with negation handling, sentences that have negative connotations have more negative meanings.

After conducting experiments and getting results for testing sentiment analysis for Indonesian people's opinions about covid-19 on Twitter with negation handling, this study can draw several conclusions: The addition of negation handling in pre-processing data is quite helpful to improve classification performance even though the accuracy is not maximized. It can be seen in Figure 4.5.4 at the point of testing the method that the increase in accuracy results only increases by only about 0.06%. Accuracy results are not maximized but the addition of negation handling gives more meaning to the polarity of the sentences in the document. For example, in the dataset table where the negation has been added, the sentence has the label "_neg". The proposed method is more suitable for use on datasets that have only two classes or binary classes when viewed from the results of the MCC evaluation matrix (Mathew Coefficient Correlation).

For future work, it is possible to improve the classifier performance to enhance the performance of the classifier algorithm. This study uses the scope of the negation of Indonesian only, maybe for further research it can use the scope of English as well.

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