INTEK Jurnal Penelitian
Vol. 11, No. 1, pp. 44-50, April 2024

Analyzing Public Sentiments on Disaster Relief Efforts Through Social Media Data

Muhammad Rafi Fakhruddin[1,*,a], Rifki Wijaya[1,b], and Moch. Arif Bijaksana [1,c]
[1] Department School of Computing, Telkom University, Jl. Telekomunikasi No. 1, Terusan Buah Batu, Bandung, Jawa Barat, Indonesia, 40257
[*,a] rafifakhruddin@student.telkomuniversity.ac.d (Corresponding Author), [b] rifkiwijaya@telkomuniversity.ac.id, [c] arifbijaksana@telkomuniversity.ac.id

***Abstract*—Social media has become a source of quick but not necessarily accurate information. Especially in social media X, which is often used to share information. This research aims to conduct sentiment analysis on posts related to natural disasters that aim to maximize assistance to victims of natural disasters. This research takes datasets from tweets on social media X, the data will be labeled into positive and negative. And then the preprocessing process will be carried out, in this study, categorization will be carried out on each tweet related to the category, then the data will be divided into training and testing. Then the Term Frequency-Inverse Document Frequency (TF-IDF) feature is used to assist in reducing the weight of words that often appear in the dataset, The next step involves designing a system with a focus on applying the Support Vector Machine (SVM) Polynomial Kernel algorithm which becomes a classifier which will later be used to find the best hyperline or decision boundary that divides each review into two classes, namely positive tweets and negative tweets. Then obtained with a value of Precision of 74.28%, Recall 97.82%, F1-Score 84.44%, and Accuracy of 80.01%. This research is expected to provide involvement in making a fast and effective decision for victims of natural disasters.**

***Keywords*—Sentiment analysis, SVM, Natural Disaster, Social Media X**

I. Introduction

Natural disasters in Indonesia very familiar, examples of natural disasters that have occurred are tsunamis, earthquakes, landslides, and other natural events. According to Law Number 24 of 2007 concerning Disaster Management, natural disasters are events that occur due to natural events [1]. There are many ways to solve the problem of natural disasters, fast information can be a solution. Nowadays information spreads very easily on the internet through social media, social media especially X has become a social media that is widely used to share information. It is also important to analyze the hashtags given to each post in X so that the hashtags are relevant to the post, so it is also very important to do a classification of hashtags that are relevant and irrelevant to the disaster. Hashtag classification can help some parties such as the government or disaster management agencies to get more accurate information. From this information, direct monitoring, coordination and sending assistance needed by communities affected by natural disasters can be done.

In this research, a sentiment analysis of natural disasters will be carried out, especially in the natural disasters of the Cianjur earthquake, floods, and erupting Ruang mountains. And the data to be used are hastags from X media. Sentiment analysis or opinion mining is used one of them to support decision making by extracting and analyzing text, and identifying positive and negative opinions [2], This research will produce positive and negative classifications, the analysis will also be carried out using the Support Vector Machine (SVM) method and also using the Term Frequency-Inverse Document Frequency (TF-IDF) feature. Some sentiment analysis research uses Support Vector Machine, this method is the best among several other methods because it is able to compute data with high dimensions so that the resulting accuracy rate is better [3]. Data from X social media will also be categorized into food, water, medical emergency, shelter, electricity, evacuation routes, clothes, and neutral. With these categories, it will help the government and disaster management agencies to know what is needed by victims of natural disasters based on reports on social media X from the community. So that these parties can be more effective in providing assistance.

Machine learning research on sentiment analysis is general used in recent years, such as research [4] doing a

DOI: http://dx.doi.org/10.31963/intek.v11i1.4773

comparison between Support Vector Machine and Logistic Regression for disaster classification. between Support Vector Machine and Logistic Regression for natural disaster classification. And the dataset used comes from twitter social media. After labelling and feature extraction of 1309 disaster tweets, 89 emergency tweets, 168 non-emergency tweets were obtained, and 1052 irrelevant tweets. and this study's results demonstrate that Support Vector Machine and Logistic Regression are used to classify natural disasters. The results of this study show that Support Vector Machine has an accuracy of 80.41%, while the Logistic Regression method has an accuracy of 63.36%,

In research [5], by combining feature extraction methods word2vec classification Support Vector Machine with a total data of 10,000 reviews data taken from movie reviews. the best result with 78.74% f1-score, the best result is due to the higher the higher the dimension, the results of the vocabulary formed by the word2vec model will be the higher the variation, thus causing the accuracy to optimizing.

In research [6], sentiment analysis regarding post-disaster tweets that have not been classified. Therefore, the classification of data into positive or negative categories using the Naïve Bayes Classifier algorithm. Bayes Classifier algorithm. From the results of the classification that has been carried out, the results are positive results can mean that assistance based on these categories has been fulfilled while negative is less or needed. This research also uses The results of this test obtained an accuracy value for unigram of 76.67%, 84.44%, 90.00% and 93.33%. While the accuracy value for bigram is 64.17%, 68.89%, 75.00%, 86.67%. From the four tests, the results obtained accuracy is for unigram 93.33% and bigram 86.67%. Consequently, it can be said that the accuracy value of unigram is higher than bigram.

II. Research Methodology

A. System Design

This process illustrates the system that will be constructed and applied in this research, The following block diagram that has been prepared can be seen in Figure 1.

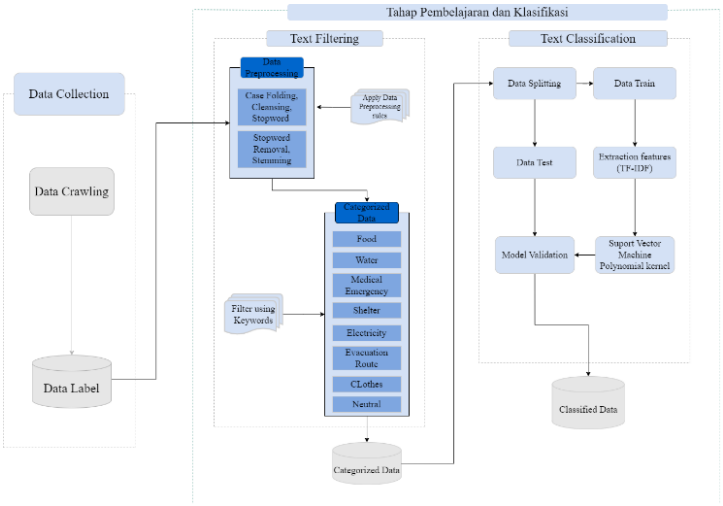

Figure 1. System Design

B. Dataset

In this process, a dataset from social media X is taken. The data taken amounts to approximately 6.147 data. Datasets taken with different time ranges, The Cianjur earthquake was taken from November 11, 2022 to January 4, 2023, while the floods were taken from July 24, 2019 to May 14, 2024, and finally the data on the eruption of Mount Ruang was taken from May 1, 2024 to May 14, 2024. after which the data is labelled 1 as positive and -1 as negative. The dataset is labeled with the researcher's opinion, labeling with opinion is one of the best ways. because there is no suitable dictionary to label related to this natural disaster. The dataset taken from social media X, taken from Indonesian tweets, because the target in this study helps the Indonesian people. In Table 1 sample of the dataset is show below.

Table 1 Dataset

Label	Tweet
1 (Positive)	muhammadsaewad baca beritanya sampe tuntas pak itu sifatnya insidentil utk sumbang gempa cianjur diusulkan oleh sejumlh ormas nu muhammadiyah mui dsb sementara pjbt gub sekadar mengizinkan sifatnya pun sukarela
-1 (Negative)	Tololllll itu gabungan infak untuk gempa cianjur

DOI: http://dx.doi.org/10.31963/intek.v11i1.4773

After doing all the labelling of the 6.147 datasets, in the study obtained a total of 3.524 positive tweets and 2.623 negative tweets. The number of positive and negative tweets can be seen in Figure 2.

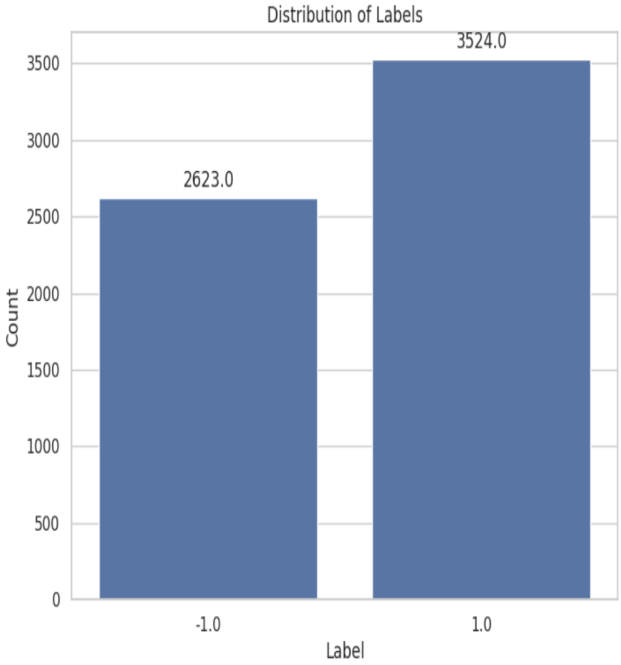

Figure 2. Sentiment Distribution.

C. *Prepocessing*

The next step is Preprocessing. Preprocessing is a process to prepare the text so that it can be transformed into a more structured one [7]. The preprocessing stages carried out are Cleansing, Case Folding, Tokenization, Stopword Removal, and Stemming. preprocessing stage can be seen in Figure 2.

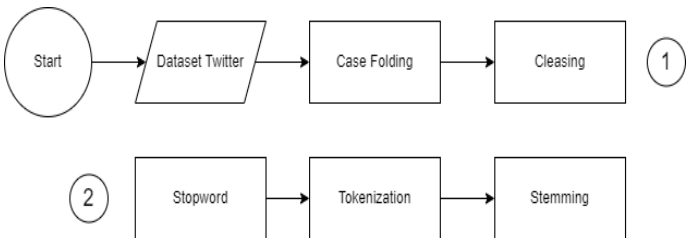

Figure 3. Preprocessing Flowchart

1) Case Folding : at this stage Case Folding aims to convert uppercase letters into lowercase letters [8]. case folding examples as in Table 2.

Table 2. Case Folding

Before Case Folding	After Case Folding
ratusan warga di padang pariaman sumbar terisolir akibat jembatan yang runtuh diterjang banjir bandang newsupdate https tcoqioddqqg3q.	ratusan warga di padang pariaman sumbar terisolir akibat jembatan yang runtuh diterjang banjir bandang newsupdate https tcoqioddqqg3q
pasca gempa bumi cianjur kemkominfo terus lakukan pemulihan jaringan telekomunikasi yg terdampak bencana platejohnny	pasca gempa bumi cianjur kemkominfo terus lakukan pemulihan jaringan telekomunikasi yg terdampak bencana platejohnny

2) Cleansing : in the Cleansing stage the data will be cleaned, because the data taken is not necessarily clean [9]. this process is useful for removing URLs, numbers, and punctuation. Table 3 below is a Cleansing example.

Table 3. Cleansing

Before Cleansing	After Cleansing
ratusan warga di padang pariaman sumbar terisolir akibat jembatan yang runtuh diterjang banjir bandang newsupdate https tcoqioddqqg3q	ratusan warga di padang pariaman sumbar terisolir akibat jembatan yang runtuh diterjang banjir bandang newsupdate
pasca gempa bumi cianjur kemkominfo terus lakukan pemulihan jaringan telekomunikasi yg terdampak bencana platejohnny	pasca gempa bumi cianjur kemkominfo terus lakukan pemulihan jaringan telekomunikasi yang terdampak bencana

3) Stopword : The third step will do Stopwords, to eliminate words that often appear and are not very used. and also prevent Stopwords from affecting the results [10]. Table 4 below is a stopword example.

Table 4. Stopword

Before Stopword	After Cleansing
ratusan warga di padang pariaman sumbar terisolir akibat jembatan yang runtuh diterjang banjir bandang newsupdate	ratusan warga padang pariaman sumbar terisolir akibat jembatan runtuh diterjang banjir bandang newsupdate
pasca gempa bumi cianjur kemkominfo terus lakukan pemulihan jaringan telekomunikasi yang terdampak bencana	pasca gempa bumi cianjur kemkominfo pemulihan jaringan telekomunikasi terdampak bencana

DOI: http://dx.doi.org/10.31963/intek.v11i1.4773

4) Tokenization : The next stage is Tokenization, where this process will break the text into small parts called "tokens". Tokenization is beneficial to computer science [11]. Table 5 is an example of tokenization.

Table 5. Tokenization

Before Tokenization	After Tokenization
ratusan warga padang pariaman sumbar terisolir akibat jembatan runtuh diterjang banjir bandang newsupdate	“ratusan”, “warga”, “padang”, “pariaman”, “sumbar”, “terisolir”, “akibat”, “jembatan”, “runtuh”, “diterjang”, “banjir”, “bandang”, “newsupdate”
pasca gempa bumi cianjur kemkominfo pemulihan jaringan telekomunikasi terdampak bencana	“pasca”, “gempa”, “bumi”, “cianjur”, “kemkominfo”, “pemulihan”, “jaringan”, “telekomunikasi”, “terdampak”, “bencana”

5) Stemming : The last stage is Stemming, this aims to return the word to its basic form. stemming examples can be seen in Table 6 below.

Table 6. Stemming

Before Stemming	After Stemming
“ratusan”, “warga”, “padang”, “pariaman”, “sumbar”, “terisolir”, “akibat”, “jembatan”, “runtuh”, “diterjang”, “banjir”, “bandang”, “newsupdate”	“ratus”, “warga”, “padang”, “pariaman”, “sumbar”, “isolir”, “akibat”, “jembat”, “runtuh”, “terjang”, “banjir”, “bandang”, “newsupdate”
“pasca”, “gempa”, “bumi”, “cianjur”, “kemkominfo”, “pemulihan”, “jaringan”, “telekomunikasi”, “terdampak”, “bencana”	pasca", "gempa", "bumi", "cianjur", "kominfo", "pulih", "jaring", "telekomunikasi", "dampak", "bencana"

D. Data Category

After the preprocessing stage has been completed and the data is easily processed by the algorithm, the data will be categorized. In this process, a grouping is carried out which aims to make data into smaller groups based on a certain equation. An example of data categorization is as shown in the table 7 below.

Table 7. Data Category

Category	Tweet
Food	Presiden mbz kirim bantuan makanan untuk korban gempa cianjur
Water	bandara samrat pastikan airside bersih dari abu vulkanik gunung ruang
Medical Emergency	b braun indonesia kirimkan alat medis untuk penanganan gempa cianjur
Shelter	bupati cianjur yang paling dibutuhkan pengungsi korban gempa adalah tenda kecil bupati cianjur yang paling dibutuhkan pengungsi korban gempa adalah tenda kecil
Electricity	pln semoga listrik di lokasi gempa cianjur segera menyala
Evacuation Route	sebanyak kk korban gempa cianjur mengungsi di garut
Clothes	radioelshinta jokowi jaket nya bagikan ke korban gempa cianjur pak
Neutral	peduli sesama ikasmansa pekanbaru galang dana untuk korban gempa cianjur

E. Data Splitting

In this stage, we will split the 6.147 datasets into two parts training data and testing data. 80% will be training data consisting of 4.917 tweets, and 20% will be the test data consisting of 1.230 tweets. It is important to do data splitting because, the researcher set a ratio of 8:2 in data splitting, Data splitting will also facilitate the modeling process [12].

F. Term Frequency-inverse Document Frequency

The next step will be featuring extraction. In this research, Term Frequency-Inverse Document Frequency will be used to analyze the text. And the text will later be converted into a numerical representation that can be processed by the algorithm. TF-IDF is a combination of different words namely Term Frequency and Inverse Document Frequency [13].

DOI: http://dx.doi.org/10.31963/intek.v11i1.4773

$$TF - IDF = TF \times IDF \quad (1)$$

$$IDF = log \frac{N}{DF} \quad (2)$$

The frequency of word occurrence (TF) in a document shows how important a word is in a document. and the more documents that contain a term, the higher its weight [14]. (N) presented the number of sentences, whereas (IDF) helps to lower the weight of words that appear a lot in the document.

G. Support Vector Machine

Support Vector Machine (SVM) is a machine learning algorithm that works on the principle of Structural Risk Minimization (SRM) with the goal of finding the optimal hyperplane that separates two classes in the input space [15]. SVM will also compare a parameter selection to a standard set of discrete values called the candidate set [16]. The linear of an SVM is the kernel, which will separate the two classes [17]. Here is the Figure. 4.

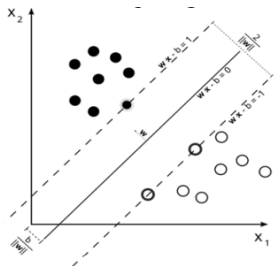

Figure 4. Kernel Support Vector Machine [17]

In this research, the SVM method will be very important, which will be used to find the best hyperline or decision boundary that divides each review into two classes, namely positive tweets and negative tweets. SVM has become a widely used tool for classification, with great flexibility covering many data science scenarios [18]. And also, in this research will be used Polynomial Kernel, Polynomial kernel are used to transform data to a higher dimensional space. [19]. This kernel is used when the data is not liner-separated [20], where the separation between classes cannot be well defined in low dimension.

H. Confusion Matrix

To evaluate the performance of the SVM method, the confusion matrix will be used, which is included in supervised learning in artificial intelligence [21]. Confusion matrix works to see the results comparison of the classification by the model using the actual outcomes of the classification. The shape of the confusion matrix will be a matrix table that will give an overview of the performance of the classification method in the testing data with known true values [22].

1. Recall:

$$R = \frac{TP}{TP + FN} \quad (3)$$

Recall is an evaluation metric to measure the model's ability to correctly identify all positive instances. It also reflects the effectiveness of the model in addressing each sentiment type [23]. (TP) means True Positive and (FN) means False Negative. which will be summed up like the formula above, and produce Recall.

2. Precision:

$$P = \frac{TP}{TP + FP} \quad (3)$$

Precision is an evaluation metric, to show how many instances have positive predictions. (TP) means True Positive and (FP) means False Positive. then will be summed and produce Precision.

3. F1-Score

$$A = 2 \times \frac{Precison \times Recall}{Precision + Recall} \quad (5)$$

F1-Score will combine precision and recall into a single value, F1-Score provides a more holistic picture of the performance of a classification model [24]. to find Accuracy, will sum the Precision and recall values

III. Results and Discussion

In the research, the datasets that will be taken and used are tweets with the hashtags Cianjur earthquake,

DOI: http://dx.doi.org/10.31963/intek.v11i1.4773

flood, and Mount Ruang eruption. The successful data from the three hashtags amounted to 6.147 tweets, and later the datasets from the three hashtags will be combined. After that the dataset will be labeled manually, label 1 will present positive and -1 will present negative. And there are 2.623 as negative tweets and 3.524 as positive tweets. After the dataset has been labeled, it will enter the preprocessing stage, namely case folding, cleansing, stopwords, tokenization, and stemming. After that, the dataset will be categorized manually, by looking for words related to the category. The categories in this research include Food, Water, Medical emergency, Shelter, Electricity, Evacuation route, Clothes, and Neutral. And the results of tweets that have been categorized can be seen in Table 8.

Table 8. Data Category Result

Category	Result
Food	306
Water	21
Medical emergency	214
Shelter	351
Electricity	35
Evacuation route	562
Clothes	29
Neutral	4.629

And the next stage will be data splitting with a ratio of 8:2 consisting of 80% training data (4.917 data) and 20% testing data (1.230 data). Furthermore, the training data will be analyzed for the performance of the TF-IDF feature which functions to reduce the weight of words, thus emphasizing words that are more unique or rarely appear in addition, it can convert words into numerical representations. Then after the data has been successfully extracted, Support Vector Machine Polynomial Kernel will be used to perform Classification. The processes mentioned will be concluded by looking at the evaluation results using Confusion Matrix.

Table 9. Result Confusion Matrix

	Precision	Recall	F1-score	Accuracy
SVM Kernel Polynomial	74.28%	97.82%	84.44%	80,01%

Based on this Table IX which presents the Confusion Matrix which contains, Precision, Recall, F1-Score, and Accuracy. Support Vector Machine Polynomial Kernel classification that uses TF-IDF features gets very good results with a value of Precision of 74.28%, Recall 97.82%, F1-Score 84.44%, and Accuracy of 80.01%. From 6.147 datasets that have gone through several processes, Support Vector Machine Polynomial Kernel using TF-IDF features can successfully classify.

IV. Conclusion

In the research that has been done from a dataset taken from social media X, which consists of 6.147 tweets using the hashtags Cianjur Earthquake, Flood, and Mount Ruang Eruption. It can be concluded that the dataset was successfully collected and labeled manually, with 2,623 negative tweets and also obtained 3,524 positive tweets. In this research TF-IDF helps to improve the performance of the classification model. The data that has been extracted using TF-IDF features is then used to train the Support Vector Machine model with Polynomial Kernel.

Evaluation results that have been obtained using Confusion Matrix, arguably shows very good performance by getting a Precision value of 74.28%, Recall of 97.82%, F1-Score of 84.44%, and Accuracy of 80.01%. It can be concluded that the Support Vector Machine classification model with Polynomial Kernel using TF-IDF features works very well in classifying disaster-related tweets and also a large dataset. It is hoped that this research can help victims of natural disasters and related parties to help the needs of victims of natural disasters.

Suggestions for further research are to explore to find classification models or features that are more effective than Support Vector Machine. Future research can provide great insight into the performance of classification models.

Acknowledgement

I would like to express my deepest gratitude to my two supervisors, who have played a very important role in this research because they provided a lot of input and corrections in this research. I am also grateful to my colleagues who also helped in this research. And of course, the writers who are references in this research. Hopefully this research can be useful in the future.

DOI: http://dx.doi.org/10.31963/intek.v11i1.4773

References

[1] V. R. Prasetyo, G. Erlangga, and D. A. Prima, "Analisis sentimen untuk identifikasi bantuan korban bencana alam berdasarkan data di Twitter menggunakan metode Kmeans dan Naïve Bayes," J. Teknol. Inform. dan Ilmu Komput. (JTIIK), vol. 10, no. 5, pp. 1055-1062, 2023.

[2] M. Lestandy, A. Abdurrahim, and L. Syafa'ah, "Analisis sentimen Tweet vaksin COVID-19 menggunakan Recurrent Neural Network dan Naïve Bayes," J. RESTI (Rekayasa Sistem dan Teknol. Inform.), vol. 5, no. 4, pp. 802-808, 2021.

[3] P. Arsi and R. Waluyo, "Analisis sentimen wacana pemindahan ibu kota Indonesia menggunakan algoritma Support Vector Machine (SVM)," J. Teknol. Inf. dan Ilmu Komput., vol. 8, no. 1, p. 147, 2021.

[4] K. W. Gusti, "Perbandingan metode Support Vector Machine dan Logistic Regression untuk klasifikasi bencana alam," Informatik: J. Ilmu Komput., vol. 19, no. 2, pp. 134-140, 2023.

[5] Y. S. Triyantono, S. A. Faraby, and M. Dwifebri, "Analisis sentimen terhadap ulasan film menggunakan word2vec dan SVM," eProceedings of Engineering, vol. 8, no. 4, 2021.

[6] I. F. Rozi, A. T. Firdausi, and K. Islamiyah, "Analisis sentimen pada Twitter mengenai pasca bencana menggunakan metode Naïve Bayes dengan fitur N-Gram," Jurnal Informatika Polinema, vol. 6, no. 2, pp. 33-39, 2020.

[7] J. W. Iskandar, J. Widyadhana, and Y. Nataliani, "Perbandingan Naïve Bayes, SVM, dan k-NN untuk analisis sentimen gadget berbasis aspek," Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 5, no. 6, pp. 1120-1126, 2021.

[8] M. A. Rosid, et al., "Improving text preprocessing for student complaint document classification using Sastrawi," IOP Conference Series: Materials Science and Engineering, vol. 874, no. 1, IOP Publishing, 2020.

[9] M. Zalukhu, "Analsis dan implementasi metode Naïve Bayes dan SVM pada sentimen pemilihan calon Presiden RI," KETIK: J. Informatika, vol. 1, no. 01, pp. 18-26, 2023.

[10] A. E. Budiman and A. Widjaja, "Analisis Pengaruh Teks Preprocessing Terhadap Deteksi Plagiarisme Pada Dokumen Tugas Akhir," Jurnal Teknik Informatika Dan Sistem Informasi, vol. 6, no. 3, pp. 475-488, 2020.

[11] S. Vijayarani and R. Janani, "Text mining: open source tokenization tools-an analysis," Advanced Computational Intelligence: An International Journal (ACII), vol. 3, no. 1, pp. 37-47, 2016.

[12] R. Koch, The 80/20 Principle: The Secret of Achieving More with Less: Updated 20th Anniversary Edition of the Productivity and Business Classic. Hachette UK, 2011.

[13] S. Qaiser and R. Ali, "Text mining: use of TF-IDF to examine the relevance of words to documents," International Journal of Computer Applications, vol. 181, no. 1, pp. 25-29, 2018.

[14] S. Y. Pangestu, Y. Astuti, and L. D. Farida, "Algoritma Support Vector Machine Untuk Klasifikasi Sikap Politik Terhadap Partai Politik Indonesia," Jurnal Mantik, vol. 3, no. 1, pp. 236-241, Jun. 2019. [Online].Available:http://iocscience.org/ejournal/index.php/mantik/article/view/173. Accessed on: Apr. 22, 2024.

[15] O. I. Gifari, et al., "Analisis Sentimen Review Film Menggunakan TF-IDF dan Support Vector Machine," Journal of Information Technology, vol. 2, no. 1, pp. 36-40, 2022.

[16] H. Wang dan D. Hu, "Comparison of SVM and LS-SVM for regression," dalam 2005 International Conference on Neural Networks and Brain, vol. 1. IEEE, 2005.

[17] D. Maulina dan R. Sagara, "Klasifikasi artikel hoax menggunakan support vector machine linear dengan pembobotan term frequency-Inverse document frequency," Jurnal Mantik Penusa, vol. 2, no. 1, 2018.

[18] A. Mechelli dan S. Vieira, eds., Machine Learning: Methods and Applications to Brain Disorders. Academic Press, 2019.

[19] P. Panavaranan dan Y. Wongsawat, "EEG-based pain estimation via fuzzy logic and polynomial kernel support vector machine," dalam The 6th 2013 Biomedical Engineering International Conference. IEEE, 2013.

[20] H. Al Azies, D. Trishnanti, dan E. M. PH, "Comparison of kernel support vector machine (SVM) in classification of human development index (HDI)," IPTEK Journal of Proceedings Series, vol. 6, pp. 53-57, 2019.

[21] M. K. Delimayanti, et al., "Pemanfaatan Metode Multiclass-SVM pada Model Klasifikasi Pesan Bencana Banjir di Twitter," Edu Komputika Journal, vol. 8, no. 1, pp. 39-47, 2021.

[22] A. R. D. Pratiwi dan E. B. Setiawan, "Implementation of rumor detection on Twitter using the SVM classification method," Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi), vol. 4, no. 5, pp. 782-789, 2020.

[23] B. W. Rauf, "Sentimen Analisis Pertambangan Di Konawe Utara Dengan Metode Naïve Bayes," dalam Prosiding Seminar Nasional Pemanfaatan Sains dan Teknologi Informasi, vol. 1, no. 1, 2023.

[24] L. Geni, E. Yulianti, dan D. I. Sensuse, "Sentiment Analysis of Tweets Before the 2024 Elections in Indonesia Using IndoBERT Language Models," Jurnal Ilmiah Teknik Elektro Komputer Dan Informatika (JITEKI), vol. 9, no. 3, pp. 746-757, 2023.

DOI: http://dx.doi.org/10.31963/intek.v11i1.4773