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# Sentimen Analysis Social Media for Disaster using Naïve Bayes and IndoBERT

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***Abstract*—The rapid advancement of information and communication technology has resulted in a significant surge in data, especially text data from social media platforms. This paper presents a sentiment analysis approach using IndoBERT and Naïve Bayes algorithms to classify sentiment related to natural disasters, specifically from a dataset of tweets derived from social media platform X. The focus of this research is to categorize tweets as positive and negative sentiment to provide useful insights in improving disaster response and management, with a focus on tweets related to earthquakes, floods, and the eruption of Mount Merapi. The goal is to assist the government in allocating aid more efficiently and understanding public sentiment during disasters. The methodology used includes data collection, data preparation, labeling, categorization, word weighting using tf-idf, data separation, and classification using Naïve Bayes and IndoBERT algorithms. The results showed that IndoBERT achieved 91% accuracy, while Naïve Bayes achieved 74% accuracy. The study highlights the potential of sentiment analysis in improving disaster preparedness and more effective response strategies.**

***Keywords: Sentiment Analysis, IndoBERT, Naïve Bayes, Social Media, Disaster Management, Natural Disasters, X***

## I. Introduction

The rapid development of information and communication technology in the world is inseparable from web service providers that offer diverse information. This information, which leads to an increase in data, The increasing need for data and information encourages people to develop new technologies so that data and information processing can be done easily and quickly, one of which is in terms of using social media applications, mostly in the form of text data, can be a highly potential source to be further explored[1]. In this paper, we look at one popular platform called X and build a model to classify "X" into positive and negative sentiments[2]. X is one of the popular social media platforms worldwide. It is a web-based platform that allows users to share short messages. X also has a significant influence in shaping public opinion and has become an important source of news in the digital era. Messages or posts conveyed by users can contribute to enhancing responses and efforts in facing disasters. This research will focus on the sentiment analysis of natural disasters.

Natural disasters are disasters that can cause great losses to life, the environment, and property. Most of them are caused by extreme natural phenomena that cannot be completely avoided. With the right understanding, planning, and action, the impact can be minimized, and humanity can be better prepared to deal with it. Some of these natural disasters are earthquakes, floods, and eruptions of Mount Merapi.

1) Earthquakes are geological phenomena that occur when energy stored in the earth's crust is suddenly released, causing vibrations on the earth's surface.

2) Flooding is a natural phenomenon caused by the evaporation of water that exceeds the normal capacity of a river, lake, or watershed.

3) The eruption of Mount Merapi is a natural phenomenon that occurs on the island of Java, Indonesia, involving the release of gases, lava, and volcanic material. The impact can vary from small to large scales, significantly affecting the life and wealth around it. The

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study focuses on the analysis of tweets related to the eruption of Mount Merapi on social media platform X, which is key to understanding social dynamics during and after natural disasters. With the main goal of classifying the positive and negative sentiment of the tweets, with the hope of providing in-depth insights for future disaster response and risk management efforts.

However, considering the overwhelming number of posts, manual analysis becomes a very difficult task. One method that can be used to manage these posts is by transforming them into useful messages to enhance their usability by applying sentiment analysis.

Sentiment analysis is the process of automatically understanding and managing textual data to obtain information, by leveraging sentiment analysis and automating these interactions, you can definitely dig into various fragments of your business clients and improve your understanding of sentiment in these segments[3]. One of the Machine Learning methods that can be used in sentiment analysis is the Naïve Bayes algorithm. Naïve Bayes is a classification method based on statistics and Bayesian theorem. It relies on the assumption of feature independence. In sentiment analysis, it is used to differentiate sentiments in tweets (positive, negative, or neutral) by using the text within the tweets as the main features[4].

The objective of this research is to categorize data from Twitter into meaningful categories that can be utilized to direct aid to specific locations. Additionally, the government can use this data to assess positive and negative sentiments that emerge on Twitter during disasters. This sentiment analysis can provide insights into the general state of the population, enabling the government to be more responsive to the needs of its citizens. Furthermore, the identification of specific categories such as water supply and evacuation routes represent a novel approach in detecting and understanding the community's situation during disasters, thereby enhancing disaster response and management strategies. Just like categorizing data samples is in research[5].

The study[6] using the Modified Naïve Bayes classification can classify academic performance by research activities better than decision trees and regular Naïve Bayes, 96.15% and 94.23%, respectively. Nevertheless, the results of this study conform to the initial classification for university research office level before being submitted to the respective national education authorities for further evaluation. This research provides deeper insights into the classification of tweets containing hate speech by X users in Indonesia.

## II. Research Methodology

### A. System Design

The research main target is to analyze the public sentiment on X on earthquake in Indonesia. The designed system can be seen in the Figure 1 below.

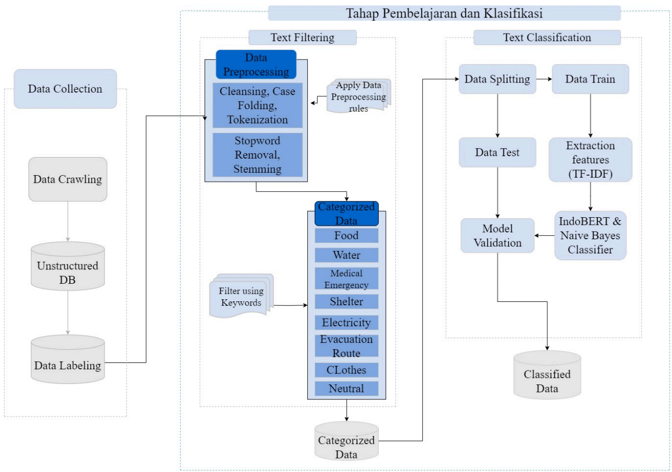


Figure 1 Flowchart of designed system

### B. Data Crawling

In this study, data was collected from the X social media application from 2012 to 2024 through data crawling. The collected dataset consists of Indonesian validation data with a total of less than 12,778 data entries. Currently, the data collected is not well structured, so each entry has been labeled based on its sentiment, where positive sentiment is labeled 1 and negative sentiment is labeled -1. The labeling process is manual and semi-automatic to ensure a high level of

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accuracy. More information about the labeled dataset can be seen in Figure 2.

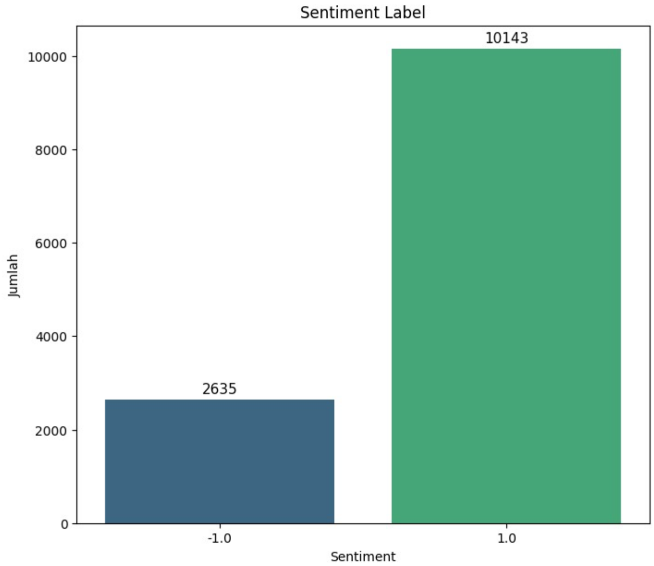


Figure 2 Sum of the Dataset

There are 10143 positive data and 2635 negative data. The example of dataset that has been labeled can be seen in the Table 1.

Tabel 1 Example of labeled dataset

| Positive | Negative |
|---|---|
| Terima kasih PLN! Kerja keras dan dedikasi kalian dalam memulihkan pasokan listrik di Pulau Tagulandang pasca-erupsi Gunung Ruang sungguh menginspirasi. #PLNuntukIndonesia jenner cicak lavani https://t.co/lw6YDE3wRm | =D1722 Kadang Hashtag orang indo tuh dipersalah gunakan sama Bot bot dan Buzzer gk guna Hashtag Gunung Ruang aja yang pengen tahu malah melenceng ke Politik sama Unsur SARA Goblok bat |
| Alhamdulillah Terimakasih untuk Dirut Pertamina KunjungiCianjur, Serahkan Bantuan untuk Korban Gempa dan pastinya bermanfaat untuk warga Cianjur https://t.co/U19FOmvpSj | @Andrisrg41 @Reesty_Cayah Baca beritanya tollol kontol amat hidup lu.itu duitnya buat korban gempa Cianjur |

*C. Data Labeling*

Manual data labeling is a process in which individuals read and label data based on specific categories. In the context of this study, manual data labeling involves reading each natural disaster-related tweet and classifying it into positive or negative sentiment. This process requires a deep understanding of the context and language used in the tweet. Although time- and labor-consuming, manual data labeling is important to ensure high quality and accuracy of data before it is used in machine learning models. These manually assigned labels will later become the basis for Naïve Bayes model training, helping algorithms to learn patterns and characteristics of each sentiment category. As done by research [7].

*D. Preprocessing*

After the dataset has been captured, the next step is preprocessing. Preprocessing is one of the stages that eliminates issues that can affect data processing results, if one of the preprocessing phases of the data is not handled properly, the machine learning algorithm will not run or may give misleading results[8].

Preprocessing is tasked with reducing the size of the feature set to make it appropriate for learning[9] In this study, the preprocessing process includes Cleansing, Case Folding, Tokenization, Stopword Removal, and Stemming. Here is an overview of the flowchart depicting the data preprocessing steps undertaken.

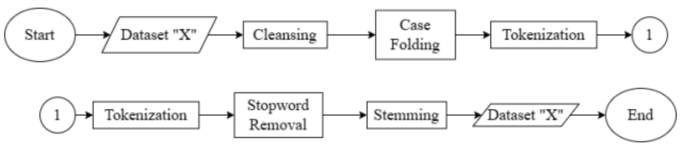


Figure 2 Processing Flowchart

*1) Cleasing :* The essential purification process entails eliminating redundant elements such as URLs, hashtags, mentioned users, punctuation, excess spaces, and so forth[10]. An illustration of this cleansing process is provided in the table below:

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Tabel 2 Cleansing Process

| Before Cleansing | After Cleansing |
|---|---|
| Perjuangan PLN Menyambung Kabel yg Terputus Usai Gempa Bumi di Cianjur https://t.co/isRqO67UX3 #Terbaru #berita #bumi #cianjur https://t.co/TOga32fZ30 | Perjuangan PLN Menyambung Kabel yg Terputus Usai Gempa Bumi di Cianjur. |
| RT @walhinasional: Walhi Sumbar: Banjir Bandang di Padang karena Illegal Logging: PADANG - Organisasi http://t.co/JN5Nee4c #walhi | rt walhinasional walhi sumbar banjir bandang di padang karena illegal logging padang organisasi http tcojn5nee4c walhi |

*2) Case Folding :* Case Folding is a process that transforms characters in text into a uniform format (usually lowercase or uppercase) to avoid sensitivity to letter case in word processing. As mentioned in[11]

Tabel 3 Case Holding Process

| Before | After |
|---|---|
| BREAKING NEWS! Banjir Bandang Terjang Sumbar \| Selasa 14 Mei 2024 https://t.co/5r4uqIKZZ0 | breaking news banjir bandang terjang sumbar selasa 14 mei 2024 https tco5r4uqikzz0 |
| @minangsedunia: Pusdalops PB Sumbar....Siaga Banjir bandang Limau Manis...Korban sementara 6 orang \| @abimYoan | minangsedunia pusdalops pb sumbar siaga banjir bandang limau manis korban sementara 6 orang abimyoan |

*3) Tokenization :* Tokenization is useful both in linguistics and in computer science, where it forms part of lexical analysis[12]. Tokenization involves dividing a set of words in a sentence, paragraph, or page into tokens, or parts of individual independent words or named entities.

Tabel 4 Tokenization Process

| Before Tokenization | After Tokenization |
|---|---|
| viral pria korban gempa cianjur pakai daster begini reaksi kang emil | ['viral', 'pria', 'korban', 'gempa', 'cianjur', 'pakai', 'daster', 'reaksi', 'kang', 'emil'] |
| polres kotamobagu peduli serahkan bantuan sembako untuk korban erupsi gunung ruang selengkapnya https tco5db6j1sifd https tcoheuitp86zm | ['polres', 'kotamobagu', 'peduli', 'serahkan', 'bantuan', 'sembako', 'untuk', 'korban', 'erupsi', 'gunung', 'ruang', 'selengkapnya', 'https', 'tco5db6j1sifd', 'https', 'tcoheuitp86zm'] |

*4) Stopword Removal :* Removing stopwords not only reduces vector space but also improves performance by increasing execution speed, calculation, and also accuracy[13]. This stopword removal process involves the removal of frequently occurring and commonly used words that do not have a significant impact on the text. An example of the removal of irrelevant words is shown in the table below.

Tabel 5 Example of Stopword

| Bahasa Stopword |
|---|
| Yang, kan, bukan, ada, tapi, ga, mau, yg, gpp, ini, kok, dan, adalah, adanya, baik, berikut, diri disini, disana, inikah, kalau, etc. |

*5) Stemming :* Stemming enables researchers to reduce all variations of words to a simple common form. The purpose of stemming is to transform similar words into the same format[14]. Table IV are the examples of stemming process.

Tabel 6 Stemming Process

| Before Stemming | After Stemming |
|---|---|
| Perjuangan PLN Menyambung Kabel yg Terputus Usai Gempa Bumi di Cianjur. | Juang PLN Sambung Kabel Putus Gempa Bumi Cianjur |
| seluruh permukaan g ruang sudah dipenuhi hasil erupsi warna gunung menjadi coklat muda https tco2vu5rldvl7 | seluruh permuka ruang sudah penuhi hasil erupsi warna gunung jadi coklat muda |

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### E. *Data Splitting*

In this step, we'll split the dataset of 12,778 entries into two parts: training data and test data. The training data will cover 80% of the total dataset, which is 10,222 train data, while the test data will cover 20%, which is 2,556 test data. This division is important because it follows an 8:2 ratio, which is based on the Pareto principle. This principle indicates that about 20% of factors contribute to about 80% of the outcomes or events that occur. Details of the results of the data separation can be seen in the Table 7:

Tabel 7 Data Splitting

| Train Data | Test Data |
|---|---|
| 10,222 | 2,556 |

### F. *Term Frequency Inverse Document Frequency (TF-IDF)*

TF-IDF, acknowledged as the premier feature extraction method for text analysis, entails converting textual documents into numerical representations[12]. The general formula for TF-IDF is depicted in the equation below[15]:

$$TF = \frac{Number\ of\ occurrences\ of\ a\ word\ in\ a\ document}{Number\ of\ words\ in\ a\ document} \quad (1)$$

$$IDF(j) = log\frac{Number\ of\ documents\ in\ the\ corpus}{Number\ of\ documents\ containing\ the\ word\ "j"} \quad (2)$$

$$TF - IDF(j) = TF \times IDF(j) \quad (3)$$

### G. *Categorical Data*

The grouping or categorization refers to organizing data into specific categories based on certain attributes. Here is the list of categories:

*1) Food :* This category addresses food needs and nutrition intake. During disasters, food supplies may be disrupted or limited, requiring special attention to ensure sufficient food availability for affected individuals.

*2) Water :* This category relates to the need for clean water supply. In natural disasters, water sources may be contaminated or difficult to access. Therefore, ensuring the availability of safe drinking water and for sanitation purposes is crucial.

*3) Medical Emergency :* This category encompasses the need for emergency medical services. It includes the supply of medications, first aid, emergency medical facilities, and medical transportation.

*4) Shelter :* Shelter or sheltering is crucial for protecting victims from hazardous environmental elements after a disaster. This can be in the form of emergency tents, shelters, or other safe and comfortable facilities.

*5) Electricity :* In disaster situations, power outages often occur, affecting various aspects of daily life. This category covers the need for electrical resources, especially for communication, lighting, and operating essential equipment.

*6) Evacuation Route :* This category involves planning and marking safe evacuation routes. Communities need to know how to leave disaster-affected areas quickly and safely.

*7) Clothes :* Security and comfort involve aspects of clothing, especially in extreme weather conditions or specific natural disasters. The availability of clothing suitable for environmental conditions is crucial.

*8) Neutral :* This category may refer to efforts of neutral resources, such as humanitarian aid and protection for all affected parties, regardless of political factors or groups.

### H. *IndoBERT*

Based on research[16], IndoBERT was chosen because it can provide higher accuracy than other machine learning and deep learning models, making it very suitable for use in the implementation of sentiment data predictions. In sentiment classification[17], IndoBERT is used to group text into categories such as positive, negative, or neutral by considering the relationship between words and sentences bidirectionally.

### I. *Naïve Bayes Classifier*

Naive Bayes is an algorithm grounded in Bayes' theorem and the assumption of independent attributes[18]. One benefit of Naive Bayes classification is its requirement to estimate only essential parameters (mean and variance of variables) from a small volume of

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training data[19]. Naive Bayes is recognized for its speed, simplicity of implementation, structural straightforwardness, and effectiveness as an algorithm. Additionally, it proves valuable for high-dimensional data due to its capability to independently estimate the probability of each feature[20].

Testing the performance of the Naïve Bayes Classifier algorithm is conducted by evaluating accuracy, precision, and recall.

## III. Results and Discussion

After successfully completing all stages, starting from Data Labeling and Preprocessing, we processed 12,778 data points through Cleaning, Stopword Removal, Stemming, and Tokenization. Once the preprocessing phase was complete, the dataset was split into training and testing sets in a 4:1 ratio. This means that 80% of the data was used for training, while the remaining 20% was used for testing the model's performance.

Next, the training data was transformed using TF-IDF (Term Frequency-Inverse Document Frequency) feature extraction, converting the textual data into numeric form suitable for machine learning algorithms. The data was then categorized and subjected to sentiment analysis using three methods: Gaussian Naive Bayes, and IndoBERT. The scenarios for the experiments are outlined in Table 8.

Tabel 8 Scenario

| **Testing Scenario** |
|---|
| **Scenario 1:** Calculating the accuracy of data using BERT |
| **Scenario 2:** Calculating the accuracy of data with Gaussian Naïve Bayes |

From Table 8 of test scenarios, there are three scenarios in this study. The first scenario is Calculating the accuracy of sentiment label data using BERT. The second scenario is comparing the entire accuracy of data with Gaussian Naïve Bayes.

Tabel 9 Result

| **Model** | **Accuracy** | **Recall** | **Precision** | **F1-Score** |
|---|---|---|---|---|
| Gaussian Naïve Bayes | 74 | 72 | 93 | 81 |
| IndoBERT | 90 | 95 | 92 | 94 |

*A. Scenario 1 : Calculating the accuracy of data using IndoBERT*

Based on Table 8, the experimental results showed excellent performance for IndoBERT, with Recall, Precision, and F1-Score reaching 90%, 95%, and 94%, respectively. These results demonstrate IndoBERT's ability to accurately recognize and classify positive and negative data. This aligns with research conducted by[21] where processed data shows that using the IndoBERT-LSTM model can work better because each encoder applies self-attention and provides output through a feed-forward network which is then continued by the next encoder.

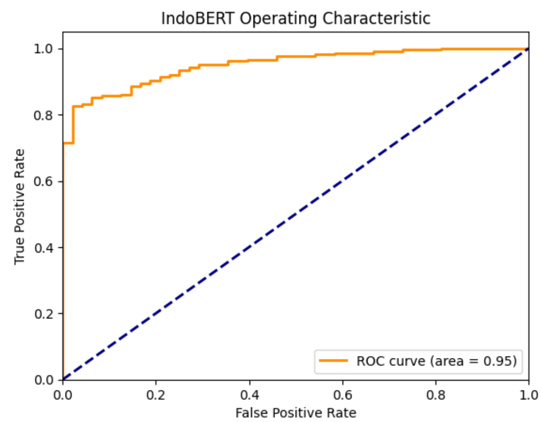


Figure 4 Result Accuracy IndoBERT

*B. Scenario 2 : Calculating the accuracy of data with Gaussian Naïve Bayes.*

Once the first scenario is complete, the next step is to conduct further experiments such as preprocessing and data categorizing and then proceed in this second scenario.

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The results, as shown in Table 8, indicate that Gaussian Naive Bayes achieved Precision, Recall, and F1-Scores of 72%, 93%, and 81%, respectively. These results suggest that Gaussian Naive Bayes handled the dataset moderately well, particularly in terms of recognizing and classifying data with a satisfactory level of accuracy. However, while the performance of Gaussian Naive Bayes is acceptable, it is still below the performance level of IndoBERT in terms of overall accuracy.

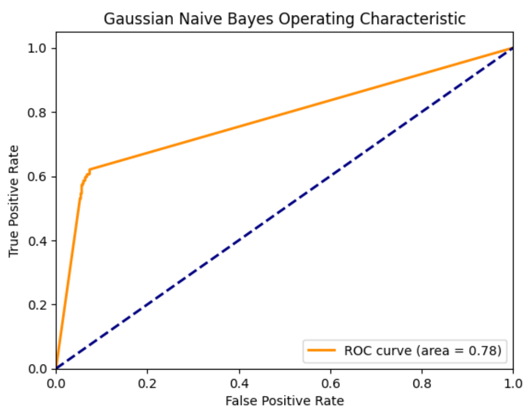


Figure 5 Result Gaussian Naive Bayes

## IV. Conclusion

In this study, we conducted sentiment analysis on social media data related to disasters using three different models: Gaussian Naive Bayes and IndoBERT. Our experiments involved preprocessing a dataset of 12,778 entries, splitting the data into training and testing sets, and applying TF-IDF for feature extraction.

The results of the experiments demonstrated that IndoBERT significantly outperformed Gaussian Naive Bayes in terms of accuracy, recall, precision, and F1-Score. Specifically, IndoBERT achieved an accuracy of 90%, a recall of 95%, a precision of 92%, and an F1-Score of 94%. In contrast, Gaussian Naive Bayes achieved an accuracy of 74%, a recall of 72%, a precision of 93%, and an F1-Score of 81%.

These findings suggest that IndoBERT is highly effective for sentiment analysis in the context of disaster-related social media data, providing superior performance compared to Gaussian Naive Bayes. Therefore, for applications requiring high accuracy in sentiment classification, IndoBERT is recommended over Gaussian Naive Bayes. Future research could explore the use of other advanced models and techniques to further enhance the accuracy and reliability of sentiment analysis in this domain.

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