

**SENTIMENT ANALYSIS OF COMMENTS ON THE  
TRAGEDY OF JULIANA MARINS' FALL ON MOUNT  
RINJANI ON APPLICATION X USING THE  
MULTINOMIAL NAÏVE BAYES METHOD**

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**Abstract**

This study analyzes public sentiment in user comments on the X (Twitter) platform regarding the tragic fall of Brazilian hiker Juliana Marins on Mount Rinjani. A total of 1,006 comments were collected between June 21 and July 11, 2025 and processed through data labeling, text preprocessing, N-Gram feature extraction, and TF-IDF weighting. The Multinomial Naïve Bayes (MNB) algorithm was applied to classify sentiments into positive, negative, and neutral categories, while Random Oversampling (ROS) was used to address class imbalance. Model performance was evaluated using accuracy, precision, recall, and F1-score, resulting in an accuracy of 85% with neutral sentiment as the dominant category. Furthermore, the use of N-Gram features improved classification performance compared to models without N-Gram, demonstrating the effectiveness of combining MNB, TF-IDF, and N-Gram for sentiment analysis of social media data in crisis-related events.

**Keywords:** Sentiment Analysis, Multinomial Naïve Bayes, TF-IDF, N-Gram, X (Twitter)

## 1. Introduction

The rapid development of information and communication technology has transformed social media into a primary platform for individuals to express opinions and respond to public issues in real time. One of the most widely used platforms for this purpose is X (formerly Twitter), which allows users to share information quickly through features such as hashtags, mentions, and retweets.

A tragic incident involving the fall of Brazilian hiker Juliana Marins on Mount Rinjani attracted widespread public attention and generated diverse reactions on social media. These responses ranged from expressions of sympathy to criticism of safety systems, tourism management, and responsible authorities. Such reactions reflect public perception, which can be systematically analyzed using sentiment analysis techniques.

Sentiment analysis, a subfield of Natural Language Processing (NLP), aims to classify textual data into sentiment categories such as positive, negative, and neutral. One of the widely used methods in sentiment classification is the Multinomial Naïve Bayes (MNB) algorithm, which is effective for text data due to its probabilistic nature and ability to handle word frequency features.

Although many studies have applied MNB for sentiment analysis, this research contributes by analyzing a real-world crisis event and comparing model performance using N-Gram and without N-Gram features. This comparison provides additional insight into the importance of contextual feature representation in improving classification performance.

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Therefore, this study aims to analyze public sentiment regarding the Juliana Marins tragedy on platform X using the Multinomial Naïve Bayes method, as well as to evaluate the impact of N-Gram feature extraction on classification performance.

## 2. Method

This study uses a sentiment analysis method with a text classification approach to determine netizens' opinions on an event on social media X (Twitter). Data is collected through a crawling process, then labeled with positive, negative, and neutral sentiments. Data processing stages include text preprocessing, feature extraction using N-Gram, and word weighting with TF-IDF. Next, the data is classified using the Multinomial Naïve Bayes algorithm with imbalanced data handling through Random Oversampling, and model performance is evaluated using a confusion matrix along with accuracy, precision, recall, and F1-score metrics.

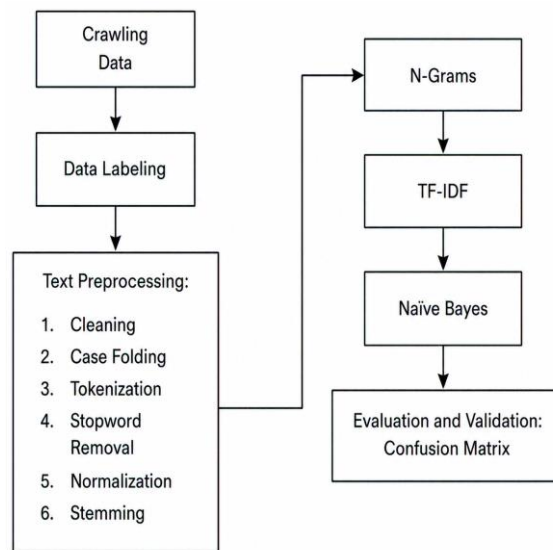


Figure 1. Research Stages

### 2.1. Data Collection

In the data collection stage, this study collected tweets from the Twitter social media platform. Data were retrieved using the keyword "Juliana Fall Case on Rinjani" and covered the period from June 21, 2025, to July 11, 2025. Through this process, a total of 1,006 tweets were obtained.

### 2.2. Text Preprocessing

. Text preprocessing is an essential stage in text data analysis prior to the classification process. The purpose of this stage is to clean and normalize the data so that it becomes more structured and ready to be analyzed by the Multinomial Naïve Bayes algorithm.

#### 2.2.1 Cleaning

Text cleaning aims to remove unnecessary characters from the text, such as punctuation marks, numbers, symbols, URLs, mentions (username), and other special characters. This process ensures that only important words remain for analysis and reduces noise in the dataset

#### 2.2.2 Case Folding

Case folding converts all characters in the text to lowercase to ensure uniformity. This process treats words such as "Juliana" and "JULIANA" as the same entity ("juliana"), thereby reducing data redundancy and standardizing text representation.

#### 2.2.3 Tokenizing

This process functions to split sentences into smaller units called tokens. Each token represents a single word unit in the text data, which will later be analyzed individually. For example, the sentence "juliana jatuh di rinjani" will be transformed into a list of tokens: [juliana, jatuh, di, rinjani]. Tokenization facilitates the identification of dominant words in comments.

### 2.2.4 Stopword Removal

At this stage, common words that do not carry significant meaning in sentiment determination such as “yang,” “dan,” “di,” and “itu” are removed from the text. Stopword removal helps reduce noise in the data and improves the effectiveness of the analysis.

### 2.2.5 Stemming

Stemming aims to reduce words to their base or root form. For example, the words “membantu,” “dibantu,” and “terbantu” are transformed into “bantu.” This process is performed so that the analysis focuses on the core meaning of each word.

## 2.3. N-Gram

N-Gram is a feature extraction technique that represents text as sequences of contiguous words. In this study, unigram and bigram models were used to capture both individual terms and short contextual word patterns.

### 2.4. TF-IDF

To determine the importance of each term in the dataset, the extracted N-Gram features were weighted using the Term Frequency–Inverse Document Frequency (TF-IDF) method.

The Term Frequency (TF) value represents how often a term appears in a document and is calculated as:

$$TF_{t,d} = \frac{f_{t,d}}{\sum f_d} \quad (1)$$

Where  $f_{t,d}$  is the frequency of term  $t$  in document  $d$ , and  $\sum f_d$  is the total number of terms in document  $d$ .

The Inverse Document Frequency (IDF) value measures the rarity of a term across the entire dataset and is calculated as:

$$IDF_t = \log \left( \frac{N}{df_t} \right) \quad (2)$$

Where  $N$  is the total number of documents and  $df_t$  is the number of documents containing term  $t$ .

The final TF-IDF weight is obtained by multiplying TF and IDF:

$$TF - IDF_{t,d} = TF_{t,d} \times IDF_t \quad (3)$$

### 2.5. Multinomial Naïve Bayes

Sentiment classification was performed using the Multinomial Naive Bayes (MNB) algorithm. This algorithm is based on Bayes' theorem and calculates the probability of a document belonging to a particular class based on term frequencies.

The posterior probability is calculated as:

$$P(c | d) = \frac{P(c) \prod P(w_i | c)}{P(d)} \quad (4)$$

Where  $c$  represents the sentiment class and  $w_i$  represents the terms in document  $d$ .

The prior probability of each class is calculated as:

$$P(c) = \frac{N_c}{N} \quad (5)$$

Where  $N_c$  is the number of documents in class  $c$ , and  $N$  is the total number of documents.

The conditional probability of a term given a class is calculated using Laplace smoothing:

$$P(w_i | c) = \frac{f_{w_i,c} + \alpha}{\sum f_c + \alpha|V|} \quad (6)$$

Where  $f_{w_i,c}$  is the frequency of term  $w_i$  in class  $c$ ,  $|V|$  is the vocabulary size, and  $\alpha$  is the smoothing parameter.

To handle class imbalance, Random Oversampling (ROS) was applied during the training process by duplicating samples from minority classes until class distributions were balanced.

### 2.6. Confusion Matrix

Model performance was evaluated using a confusion matrix, which compares predicted sentiment labels with actual labels.

Accuracy was calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

Precision, Recall, and F1-score were calculated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

$$F1-Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{10}$$

These metrics provide a comprehensive evaluation of the classification performance for each sentiment class.

## 3. Results

### 3.1. Data Collection and Sentiment Distribution

A total of 1,006 comments were collected from the X (Twitter) platform through a crawling process using Google Colab. The collected data consist of various types of user responses related to the Juliana Marins tragedy.

After manual labeling conducted by an NLP expert, the dataset was classified into three sentiment categories: negative (346 comments), positive (84 comments), and neutral (576 comments). The distribution shows that neutral sentiment dominates the dataset, indicating that most users expressed neutral opinions rather than explicit emotional responses.

	A	B	C	D	E	F	G	H	I
1	full_text								
2	Autopsi ulung di Brasil menunggal Juliana Marins meninggal 10-15 menit setelah jatuh di Gunung Rinjani akibat cedera fatal seperti: patah tulang, pangu...								
3	Evaluasi wisatawan asal Brasil Juliana Marins yang jatuh di Gunung Rinjani mendapat kritik tajam dari anggota Komisi V DPR RI. Dalam rapat bersama Kap...								
4	Anggota Komisi V DPR RI Mardiana Hanafi menyebut langkah evakuasi yang dilakukan oleh tim gabungan Basarnas dan relawan terhadap WNA Brasil yang jatru...								
5	Kontes sebelumnya: Turis Brasil Juliana Marins jatuh di Rinjani dan mela kemarahan warga Brasil terhadap Indonesia								
6	Di balik evaluasi Juliana Marins pendaki asal Brasil yang jatuh dan meninggal dunia di Gunung Rinjani ada sosok relawan dan juga tim SAR yang berjuga di...								
7	Insiden yang menimpa Juliana Marins yang jatuh di jurang Rinjani berbuntut panjang. Akibat kasus itu Menteri Koordinator Bidang Politik dan Keamanan (K...								
8	Tahu Juliana ternyata seorang pendaki pemula! Ini baratnya orang ga bisa berenang POMD ikutan berenang di kolam yg dalam? Atain? mami? gunung vulka...								
9	baw karena kejadian Juliana jatuh di gunung rinjani itu ga udah 2 minggu ini isinya gunung semua sempet mikir kapan ya keh hiking lagi keh harus hiking di...								
10	Menteri Polkam Budi Gunawan tegaskan pemerintah kini mempercepat SOP pendakian Gunung Rinjani namun insiden jatuhnya turis Brasil Juliana Marins, hr...								
11	Tanggap duka menyelumi pemakaman Juliana Marins di Niteroi Brasil. Pendaki muda itu tewas tragis usai jatuh dari lereng Gunung Rinjani Lombok. Di tang...								
12	Pemerintah Indonesia mempercepat jika pemerintah Brasil ingin melakukan investigasi bersama terkait insiden kematian warganya Juliana Marins yang di...								
13	Viral video seseorang disebut-sebut sebagai pemandu gunung atau guide Juliana Marins sedang menuruni tebing untuk tolong pendaki Brasil itu yang jatru...								
14	@manusiarombeng, @CNNIndonesia Kasus kematian Juliana Marins menjadi besar karena melibatkan diplomasi internasional: warga Brasil tewas jatuh di G...								

Figure 2. Crawled comment data from X platform

	A	B
1	full_text	label
2	Autopsi ulung di Brasil menunggal Juliana Marins meninggal 10-15 menit setelah jatuh di Gunung Rinjani akibat cedera fatal seperti: patah tulang, pangu...	neutral
3	Evaluasi wisatawan asal Brasil Juliana Marins yang jatuh di Gunung Rinjani mendapat kritik tajam dari anggota Komisi V DPR RI. Dalam rapat bersama Kap...	neutral
4	Anggota Komisi V DPR RI Mardiana Hanafi menyebut langkah evakuasi yang dilakukan oleh tim gabungan Basarnas dan relawan terhadap WNA Brasil yang jatru...	neutral
5	Kontes sebelumnya: Turis Brasil Juliana Marins jatuh di Rinjani dan mela kemarahan warga Brasil terhadap Indonesia	neutral
6	Di balik evaluasi Juliana Marins pendaki asal Brasil yang jatuh dan meninggal dunia di Gunung Rinjani ada sosok relawan dan juga tim SAR yang berjuga di...	neutral
7	Insiden yang menimpa Juliana Marins yang jatuh di jurang Rinjani berbuntut panjang. Akibat kasus itu Menteri Koordinator Bidang Politik dan Keamanan (K...	neutral
8	Tahu Juliana ternyata seorang pendaki pemula! Ini baratnya orang ga bisa berenang POMD ikutan berenang di kolam yg dalam? Atain? mami? gunung vulka...	neutral
9	baw karena kejadian Juliana jatuh di gunung rinjani itu ga udah 2 minggu ini isinya gunung semua sempet mikir kapan ya keh hiking lagi keh harus hiking di...	neutral
10	Menteri Polkam Budi Gunawan tegaskan pemerintah kini mempercepat SOP pendakian Gunung Rinjani namun insiden jatuhnya turis Brasil Juliana Marins, hr...	neutral
11	Tanggap duka menyelumi pemakaman Juliana Marins di Niteroi Brasil. Pendaki muda itu tewas tragis usai jatuh dari lereng Gunung Rinjani Lombok. Di tang...	neutral
12	Pemerintah Indonesia mempercepat jika pemerintah Brasil ingin melakukan investigasi bersama terkait insiden kematian warganya Juliana Marins yang di...	neutral
13	Viral video seseorang disebut-sebut sebagai pemandu gunung atau guide Juliana Marins sedang menuruni tebing untuk tolong pendaki Brasil itu yang jatru...	neutral
14	@manusiarombeng, @CNNIndonesia Kasus kematian Juliana Marins menjadi besar karena melibatkan diplomasi internasional: warga Brasil tewas jatuh di G...	neutral
15	Ibu Negara Brazil Haddi Pemakaman Juliana Marins Turis yang Meninggal Setelah Jatuh di Gunung Rinjani https://t.co/Eec0h3IF	neutral
16	Marsika (tim SAR dan Basarnas) juga bertaruh nyawa buat mengevakuasi korban	neutral
17	Tim SAR udah maksimal yg ga maksimal atasan2 yg ga kasih mereka fasilitas malah dipeke korupsi	negatif
18	Respect seling-selingnya untuk Tim SAR dan Basarnas. Terima	positif
19	Saat ini kabar dari bung Agam Rinjani beristirahat dahulu di Pos 2 sebelum melanjutkan perjalanan.	neutral

Figure 3. Crawled comment data from X platform

### 3.2. Text Preprocessing Results

Text preprocessing was applied to all collected comments to reduce noise and normalize textual data. The preprocessing stages included cleaning, case folding, tokenizing, normalization, stopword removal, and stemming. These steps successfully transformed raw text into a structured format suitable for feature extraction and classification.

```

                                full_text \
0 Autopsi ulang di Brasil mengungkap Juliana Mar...
1 Evakuasi wisatawan asal Brasil Juliana Marins ...
2 Anggota Komisi V DPR RI Mori Hanafi menyebut l...

                                case_folding \
0 autopsi ulang di brasil mengungkap juliana mar...
1 evakuasi wisatawan asal brasil juliana marins ...
2 anggota komisi v dpr ri mori hanafi menyebut l...
    
```

Figure 4. Cleaning Results

```

                                clean_text
0 Autopsi ulang di Brasil mengungkap Juliana Mar...
1 Evakuasi wisatawan asal Brasil Juliana Marins ...
2 Anggota Komisi V DPR RI Mori Hanafi menyebut l...

                                tokenizing
0 [autopsi, ulang, di, brasil, mengungkap, julia...
1 [evakuasi, wisatawan, asal, brasil, juliana, m...
2 [anggota, komisi, v, dpr, ri, mori, hanafi, me...

                                stemming
0 [autopsi, ulang, brasil, unkap, juliana, mari...
1 [evakuasi, wisatawan, brasil, juliana, marins,...
2 [anggota, komisi, v, dewan wakil rakyat, repub...
    
```

Figure 5. Tokenizing Results

```

                                stopword_removal \
0 [autopsi, ulang, brasil, mengungkap, juliana, ...
1 [evakuasi, wisatawan, brasil, juliana, marins,...
2 [anggota, komisi, v, dewan perwakilan rakyat, ...
    
```

Figure 6. Stemming Results

To illustrate the preprocessing process, Figure 3, Figure 4, and Figure 5 present the results of cleaning, tokenizing, and stemming, respectively. Other preprocessing steps, including case folding, normalization, and stopword removal,

were applied to all data but are not visualized due to space limitations

### 3.3. Feature Extraction and TF-IDF Weighting

After preprocessing, textual features were extracted using the N-Gram approach, consisting of unigram, bigram, and trigram combinations. This method allows the model to capture contextual information from sequences of words rather than relying solely on single terms.

TF-IDF weighting was then applied to determine the importance of each term within the document corpus. The TF-IDF results indicate that terms frequently appearing in specific documents but rarely across the corpus obtained higher weights, making them more influential during classification.

```

unigram \
0 [autopsi, ulang, brasil, ungkap, juliana, mari...
1 [evakuasi, wisatawan, brasil, juliana, marins,...
2 [anggota, komisi, v, dewan wakil rakyat, repub...
3 [konteks, turis, brazil, juliana, marins, jatu...
4 [evakuasi, juliana, marins, daki, brasil, jatu...

bigram \
0 [autopsi ulang, ulang brasil, brasil ungkap, u...
1 [evakuasi wisatawan, wisatawan brasil, brasil ...
2 [anggota komisi, komisi v, v dewan wakil rakya...
3 [konteks turis, turis brazil, brazil juliana, ...
4 [evakuasi juliana, juliana marins, marins daki...

trigram
0 [autopsi ulang brasil, ulang brasil ungkap, br...
1 [evakuasi wisatawan brasil, wisatawan brasil j...
2 [anggota komisi v, komisi v dewan wakil rakyat...
3 [konteks turis brazil, turis brazil juliana, b...
4 [evakuasi juliana marins, juliana marins daki,...
    
```

Figure 7. N-Gram feature extraction results

### 3.4. Random Oversampling Results

Random Oversampling (ROS) was applied to address the class imbalance problem in the sentiment dataset. Before ROS, the distribution of sentiment classes was uneven, with one class dominating the dataset. After ROS, each sentiment class contained an equal number of samples (460 data per class), ensuring balanced class representation.

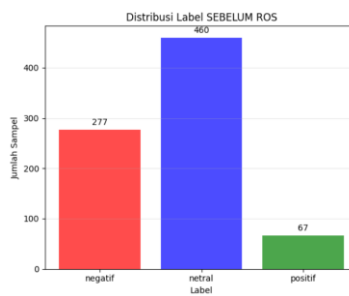


Figure 8. Label distribution before ROS

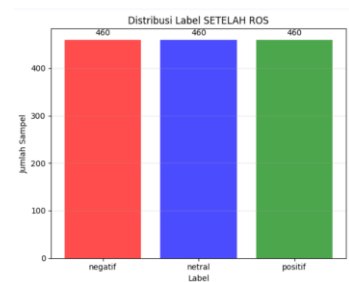


Figure 9. Label distribution after ROS

This balancing process enables the classification model to learn patterns from each class more proportionally and reduces bias toward the majority class.

### 3.5. Multinomial Naïve Bayes Classification Results

The Multinomial Naïve Bayes classifier was trained using TF-IDF weighted N-Gram features. The dataset was divided into training and testing data with a 70:30 ratio. Model evaluation was conducted using a confusion matrix and standard performance metrics.

The confusion matrix results show that the model correctly classified 125 negative, 91 neutral, and 135 positive comments. Overall, the classification performance demonstrates that the proposed model effectively distinguishes sentiment categories.

Class 'negatif':	
1. di	$P(w negatif) = 0.020245$
2. jatuh	$P(w negatif) = 0.017009$
3. berduka	$P(w negatif) = 0.015841$
4. rinjani	$P(w negatif) = 0.015069$
5. yang	$P(w negatif) = 0.014769$
Class 'netral':	
1. ini	$P(w netral) = 0.015288$
2. tim	$P(w netral) = 0.013167$
3. sar	$P(w netral) = 0.012938$
4. yang	$P(w netral) = 0.012666$
5. yg	$P(w netral) = 0.011133$
Class 'positif':	
1. yang	$P(w positif) = 0.019664$
2. tenang	$P(w positif) = 0.018190$
3. tim	$P(w positif) = 0.017329$
4. kasih	$P(w positif) = 0.016290$
5. sar	$P(w positif) = 0.015686$

Figure 10. Implementation of Multinomial Naïve Bayes

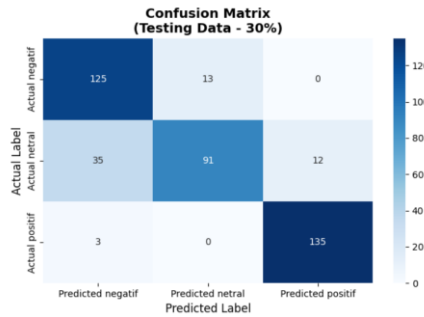


Figure 11. Confusion matrix results

### 3.6. Performance Comparison: With N-Gram vs Without N-Gram

To evaluate the impact of N-Gram feature representation, model performance was compared between using N-Gram and without using N-Gram. The evaluation results indicate that the model with N-Gram achieved better performance across all metrics.

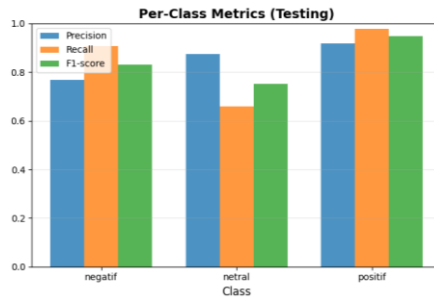


Figure 12. Evaluation results using N-Gram features

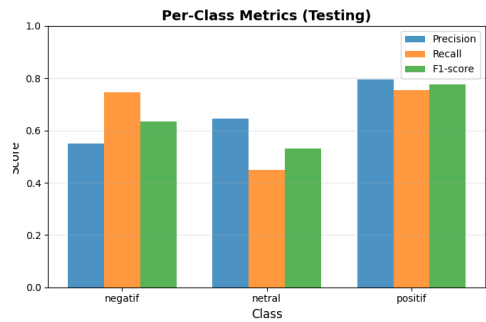


Figure 13. Evaluation results without N-Gram features

The comparison results are summarized in Table 1.

Model	Accuracy	Precision	Recall	F1-Score
With N-Gram	0.85	0.85	0.85	0.84
Without N-Gram	0.69	0.80	0.79	0.79

### 3.7. N-Gain Analysis

To quantitatively measure the improvement achieved by applying N-Gram features, N-Gain analysis was performed based on the comparison between the model with N-Gram and without N-Gram. The N-Gain results summarize the performance improvement observed after introducing contextual feature representation. As illustrated in the N-Gain figure, the obtained N-Gain value indicates a measurable performance increase from the baseline model (without N-Gram) to the enhanced model (with N-Gram). The N-Gain value falls into the *moderate* category, indicating that the use of N-Gram features provides a meaningful improvement in sentiment classification performance compared to the model without N-Gram.

## 4. Conclusion

This study analyzed netizens’ comments on the tragedy of Juliana Marins’ fall on Mount Rinjani using the X application and the Multinomial Naïve Bayes method. Data collection and preprocessing—including cleaning, case folding, tokenization, stopword removal, and stemming—were successfully performed, and the data were represented using N-Gram and TF-IDF for optimal sentiment analysis. The Multinomial Naïve Bayes algorithm achieved an accuracy of 85%, precision of 85%, recall of 85%, and F1-Score of 84%, demonstrating effective classification of comments into positive, negative, and neutral sentiments, with neutral being the most dominant.

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