ISSN 2579-7069


# A Machine Learning Approach to Indonesian Climate Change Sentiment Analysis Using Naive Bayes

Henderi[1,*], Sofa Sofiana[2]

[1]*Department of Informatics, Universitas Raharja, Indonesia*

[2]*Department of Informatics, Pamulang University, Indonesia*

(Received September 1, 2024; Revised October 15, 2024; Accepted November 30, 2024; Available online January 4, 2025)

**Abstract**

Climate change poses a significant global challenge, particularly for archipelagic nations such as Indonesia that are highly vulnerable to rising temperatures and extreme weather events. This study applies machine learning-based sentiment analysis to assess Indonesian public opinion on climate change using Twitter data. A total of 5,120 Indonesian-language tweets were collected through keyword-based scraping related to climate and weather conditions. Following text preprocessing (lowercasing, stopword removal, stemming, and cleaning), TF-IDF vectorization was used to extract the top 400 most significant terms. The dataset was divided into training (80%) and testing (20%) subsets, and a Multinomial Naïve Bayes classifier was trained to categorize sentiments into positive, neutral, and negative classes. The results show a dominance of negative sentiment (62%), primarily associated with extreme heat and storm-related events, while neutral (24%) and positive (14%) sentiments were linked to moderate weather conditions. Model evaluation achieved an F1-score of 0.95 for negative, 0.86 for neutral, and 0.83 for positive sentiment, yielding a macro-average F1-score of 0.88. The analysis also identified "panas (hot)," "hujan (rain)," and "banjir (flood)" as top lexical indicators influencing classification. Overall, the findings highlight that Indonesian public sentiment toward climate change is highly reactive to extreme weather. The study underscores the potential of Naïve Bayes as a baseline model for real-time environmental sentiment monitoring, offering valuable insights for institutions such as BMKG to enhance public communication and climate awareness strategies.

*Keywords:* Climate Change, Sentiment Analysis, Twitter, Naive Bayes, Indonesia, Public Perception

## 1. Introduction

Climate change is one of the most pressing global issues of the 21st century, with tangible impacts such as rising temperatures, sea-level rise, and increased frequency of natural disasters [1]. As an archipelagic nation, Indonesia is particularly vulnerable to these effects, making it crucial to understand public perception in order to design effective mitigation and adaptation strategies [2].

In the digital era, social media has become a primary channel for individuals to express their opinions and emotions on current issues [3]. Twitter, in particular, serves as an open and real-time platform that reflects the dynamic nature of public discourse [4]. Government agencies such as the Meteorology, Climatology, and Geophysics Agency (BMKG) actively disseminate climate-related information through their official Twitter account (@infoBMKG), which often prompts various public responses [5].

To identify public sentiment patterns on climate-related topics, sentiment analysis techniques are required to classify opinions into categories such as positive, negative, or neutral [6]. Sentiment analysis is a subfield of text mining that uses Natural Language Processing (NLP), statistical methods, and machine learning to extract subjective information from text [7]. Previous studies have shown that social media data can be effectively used to assess public opinion on environmental issues. For instance, Susilo et al. [8] analyzed Indonesian sentiment regarding biodiversity, while Wijaya et al. [9] studied public opinion on air pollution in Jakarta via Twitter. On a global level, Tatar et al. [10] applied

*Corresponding author: Henderi (henderi@raharja.info)
DOI: https://doi.org/10.47738/ijiis.v8i1.246

machine learning to understand public sentiment toward climate policies and found that negative sentiment often stems from distrust in government effectiveness.

In the field of text classification, the Naive Bayes algorithm is widely used due to its simplicity, computational efficiency, and reasonably strong performance [11]. This study, therefore, aims to classify Indonesian public sentiment toward climate change using Twitter data and the Naive Bayes algorithm. The findings are expected to provide a real-time overview of public opinion and serve as a foundation for data-driven policy development by agencies such as BMKG.

## 2. The Related Works

The issue of climate change has attracted increasing global attention due to its multifaceted impact on the environment, economy, and society. As countries face more severe weather events and ecological disruptions, researchers have turned to digital platforms to analyze how the public perceives and responds to these challenges [12]. Social media, particularly Twitter, has emerged as a valuable source of real-time public opinion data. Its open-access nature allows researchers to mine user-generated content for insights into public awareness, concern, and sentiment surrounding climate-related topics [13]. Several studies have successfully leveraged Twitter data to monitor public responses during natural disasters or policy announcements related to climate and environmental management [14].

Sentiment analysis is one of the most commonly applied techniques for interpreting textual data from social media. It involves classifying textual input into categories such as positive, negative, or neutral based on linguistic features [15]. Researchers have combined lexicon-based and machine learning approaches to improve sentiment classification accuracy, especially in noisy environments like Twitter [16]. The use of machine learning in sentiment analysis has significantly advanced with the development of NLP models such as Support Vector Machines (SVM), Logistic Regression, and neural network-based approaches [17]. Deep learning models, including LSTM and transformer-based architectures like BERT, have shown superior performance in capturing contextual nuances in text [18]. For Indonesian language processing, tools like IndoBERT and IndoNLU have provided localized NLP resources to improve classification outcomes [19].

Despite the emergence of complex models, the Naive Bayes classifier remains a popular choice for baseline sentiment classification due to its computational simplicity and acceptable performance, especially on smaller or balanced datasets [20]. Prior studies have demonstrated its effectiveness in various domains, including forest fire sentiment classification and brand sentiment analysis [21].

Visual tools such as word clouds and frequency analysis are often used to support sentiment analysis findings by identifying commonly used words or phrases associated with specific emotions [22]. However, recent studies suggest that these visualizations should be complemented with statistical validation or semantic analysis to enhance interpretability and insight generation [23]. Based on this body of literature, it is evident that integrating Twitter-based data, sentiment analysis, and machine learning algorithms—particularly Naive Bayes—can serve as a valuable method for capturing public sentiment on climate change in Indonesia. This study contributes to that growing field by applying these techniques in a localized context.

## 3. Methodology

### 3.1. Data Collection

This study collected Indonesian-language tweets related to climate and weather using a keyword-based scraping approach. Keywords such as “climate change,” “extreme weather,” “rain,” and “heat” were used to filter relevant discussions. Tweets were sourced from both public user accounts and official institutional accounts like @infoBMKG. A total of 5,120 tweets were gathered. Each tweet was manually labeled into one of three sentiment categories: positive, negative, or neutral. The annotation was conducted by two native Indonesian speakers using a consistent set of labeling guidelines. Although disagreements were resolved through discussion, no inter-annotator agreement score was formally calculated, which is acknowledged as a methodological limitation.

ISSN 2579-7069


## 3.2. Data Understanding

An exploratory analysis was conducted to understand the dataset's structure. This included examining the number of tweets, the sentiment label distribution, and the temporal patterns of sentiment changes. The sentiment distribution revealed a class imbalance: 62% of tweets were labeled negative, 24% neutral, and 14% positive. Sentiment spikes were observed during specific climate events such as heatwaves and heavy rainfall. These patterns were visualized using bar charts and time-series graphs to guide further model development and evaluation.

## 3.3. Data Preprocessing

To prepare the tweet content for classification, standard preprocessing techniques were applied. All text was converted to lowercase for normalization. Irrelevant elements such as URLs, punctuation, numbers, and special characters were removed. Stopwords were eliminated using the Sastrawi stopword list tailored for the Indonesian language. Stemming was performed with the Sastrawi stemmer to reduce each word to its root form. The final cleaned text was stored in a new column and used as input for feature extraction.

## 3.4. Feature Extraction

The cleaned text was transformed into numerical vectors using the Term Frequency–Inverse Document Frequency (TF-IDF) method. This approach assigns importance to words based on their frequency in individual tweets and their rarity across the full corpus. The top 400 most significant terms were retained to reduce dimensionality. While TF-IDF is efficient, it does not capture semantic relationships between words. Future studies may explore contextual embeddings such as Word2Vec or transformer-based models like IndoBERT to improve the model's understanding of language context.

## 3.5. Data Partitioning

The dataset was divided into training and test sets using stratified sampling to maintain class balance. Eighty percent of the data was used to train the model, while the remaining twenty percent served as the test set. This approach ensured that each sentiment category was proportionally represented in both subsets, mitigating the effects of data skewness during evaluation.

## 3.6. Model Training

The sentiment classification model was built using the Multinomial Naive Bayes algorithm. This algorithm is suitable for text data represented by discrete values, such as those generated by TF-IDF. It operates on probabilistic principles with the assumption of feature independence and is known for its simplicity and fast computation. The model was trained to classify tweets into positive, negative, and neutral sentiments. While effective as a baseline model, it does not account for semantic nuance. The absence of comparisons with other models, such as Logistic Regression, SVM, or transformer-based methods, is acknowledged as a limitation and will be addressed in future work.

## 3.7. Model Evaluation

Model performance was assessed using standard evaluation metrics. The accuracy of the model measures the proportion of correctly classified instances and is defined as:

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

TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative.

Precision indicates how many of the predicted positive instances are actually correct:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall measures the ability of the classifier to identify all relevant instances:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score is the harmonic mean of precision and recall, providing a balance between the two:

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

A confusion matrix was also generated to visualize the distribution of correct and incorrect predictions across each sentiment class. While the model achieved high accuracy, this result is treated with caution due to potential class imbalance and overfitting. Cross-validation and benchmarking with more advanced models are proposed as future work to strengthen the model's generalizability and robustness.

**4. Results and Discussion**

## 4.1. Sampling Distribution and Representativeness

Understanding which weather conditions prompt the most public engagement on social media provides crucial insight into how climate issues are perceived and prioritized by the Indonesian population. This section presents the distribution of tweet volume according to specific weather references extracted from the dataset. As summarized in Table 1, the weather condition most frequently mentioned was "Hot," with a total of 1,845 tweets, accounting for 36.0% of the overall dataset.

**Table 1.** Distribution of tweets by weather condition

| Weather Condition | Tweet Count | Percentage (%) |
|---|---|---|
| Hot | 1,845 | 36.0 |
| Rainy | 1,235 | 24.1 |
| Cloudy | 720 | 14.1 |
| Windy | 440 | 8.6 |
| Stormy | 380 | 7.4 |
| Hazy | 300 | 5.9 |
| Others | 200 | 3.9 |
| Total | 5,120 | 100.0 |

The predominance of hot weather in the dataset is likely tied to the direct and immediate discomfort experienced by individuals during heatwaves or periods of unusually high temperatures. In tropical climates such as Indonesia's, extreme heat is not only physically exhausting but can also disrupt daily activities, impact health, and affect productivity. The frequent mention of "hot" conditions on Twitter reflects this discomfort, as users turn to social media to vent frustration, share heat-related experiences, or discuss the impact on their surroundings. This observation aligns with findings in subsequent sentiment analysis, where hot weather is consistently associated with negative sentiment.

Rainy weather is the second most mentioned condition, comprising 1,235 tweets or 24.1% of the total. Rain in Indonesia is often linked to flooding, transportation delays, and infrastructure issues, especially in urban areas. As such, the high tweet volume around rain may stem from both personal inconvenience and broader concerns over weather-induced disruptions. Additionally, rainy conditions may be more visible in media and official government warnings (e.g., from @infoBMKG), prompting a surge in related public discourse.

Cloudy and windy conditions together make up approximately 22.7% of the total dataset. These weather types tend to be perceived as mild or transitional and are less likely to cause direct impact, which may explain their lower frequency in public discussions. However, the fact that they still garner significant tweet volumes suggests that even relatively benign weather changes are noteworthy to users, possibly because they serve as indicators of upcoming rain or storms.

Mentions of stormy and hazy weather are less frequent, totaling 7.4% and 5.9% respectively. These conditions, while potentially severe, may occur less frequently or be more localized, leading to reduced nationwide visibility and discourse. For example, haze from forest fires may only affect specific provinces, thereby limiting the geographic scope of public concern and online reporting. Nevertheless, such mentions should not be overlooked, as they often indicate more serious environmental degradation or health risks, especially when haze is caused by air pollution or land burning.

The "Others" category, which includes ambiguous or less common weather mentions, accounts for only 3.9% of the dataset. This small proportion suggests that most users focus their climate-related expressions on clearly identifiable weather events. The low volume also reinforces the effectiveness of keyword-based data collection, as it successfully captured the most relevant and prevalent weather topics discussed online.

The data clearly demonstrates that public discourse about climate and weather in Indonesia is heavily skewed toward immediate and physically felt phenomena—particularly heat and rain. These conditions likely generate a stronger emotional and behavioral response, driving users to engage more frequently on Twitter. This observation sets the stage for deeper sentiment-based analysis in the following sections, where we explore how different weather types correlate with expressions of positive, neutral, or negative sentiment.

## 4.2. Sentiment Distribution by Weather Type

To gain deeper insight into how different weather conditions influence public emotions and attitudes, sentiment was analyzed across the major weather types identified in the dataset. This analysis offers a more granular understanding of not just what weather conditions are most discussed (as outlined in Section 4.1), but also how people emotionally respond to them. Table 2 presents the distribution of sentiment—categorized into positive, neutral, and negative—based on the referenced weather type in each tweet.

**Table 2.** Sentiment distribution across weather types

| Weather Type | Positive | Neutral | Negative | Total |
|---|---|---|---|---|
| Hot | 120 | 325 | 1,400 | 1,845 |
| Rainy | 210 | 400 | 625 | 1,235 |
| Cloudy | 160 | 430 | 130 | 720 |
| Windy | 95 | 280 | 65 | 440 |
| Stormy | 20 | 75 | 285 | 380 |
| Hazy | 15 | 90 | 195 | 300 |
| Others | 50 | 120 | 30 | 200 |

The results reveal significant differences in emotional responses depending on the type of weather referenced. Unsurprisingly, hot weather is overwhelmingly linked to negative sentiment, with over 75% (1,400 of 1,845) of related tweets expressing dissatisfaction, discomfort, or distress. This reflects the tangible impact of high temperatures on daily life in a tropical country like Indonesia. Complaints about heat often include references to physical exhaustion, lack of productivity, and sleep disturbances, all of which drive a strong emotional reaction in online discourse.

Similarly, stormy and hazy conditions show a high proportion of negative sentiment—285 and 195 tweets respectively. These weather types are often associated with danger or health concerns. For example, storm-related tweets may discuss flooding or damage to infrastructure, while haze is frequently tied to poor air quality, respiratory issues, and broader environmental degradation (e.g., from forest fires). Though less frequent in volume compared to heat or rain, these conditions elicit a disproportionately negative reaction relative to their total mentions.

In contrast, cloudy and windy weather generated much more neutral and positive sentiment. In the case of cloudy conditions, the relatively balanced sentiment distribution—430 neutral, 160 positive, and only 130 negative—suggests that such weather is perceived as calming, comfortable, or at least non-threatening. Similarly, tweets mentioning wind often described it as refreshing or seasonal, with limited references to destructive wind events. This suggests that not all weather changes are viewed negatively; some may be appreciated or tolerated as part of the natural climate cycle.

Rainy weather, which is the second most mentioned condition overall, shows a relatively balanced sentiment profile. While 625 tweets expressed negative sentiment, a considerable number of users remained neutral (400) or even positive (210). This could be due to the dual nature of rain: it can be inconvenient and flood-inducing in cities, but also seen as soothing or beneficial for agriculture. The ambiguity of rain's impact is clearly reflected in the sentiment data.

The "Others" category, while representing a small portion of the dataset, is notable for its relatively higher percentage of positive sentiment (25%). This category includes general weather descriptions that may not trigger strong emotional reactions, such as "breezy," "cool evening," or general commentary like "nice weather today." As a result, it captures tweets that lean toward appreciation or factual observation rather than complaint.

Taken together, these findings underscore that public sentiment is not uniformly negative across all weather types. While extreme or disruptive weather—especially heat, storms, and haze—clearly trigger negative emotional responses, other conditions such as cloudy and windy weather may evoke neutral or even pleasant sentiment. These nuanced insights are critical for tailoring climate communication strategies. For instance, agencies such as BMKG may benefit from amplifying positive messages during mild weather to strengthen public trust, while focusing on risk communication and support during harsher conditions.

This sentiment-weather relationship also provides an empirical foundation for predicting emotional volatility in response to weather events, which can be integrated into early warning systems or social media monitoring tools aimed at improving disaster preparedness and climate communication outreach.

## 4.3. Weekly Sentiment Trends

Temporal analysis is crucial for understanding how public sentiment evolves in response to ongoing climate conditions and environmental events. By examining sentiment fluctuations over time, researchers can uncover patterns of emotional reactivity, identify periods of heightened concern, and assess the potential influence of real-world weather incidents on public discourse. Table 3 presents the weekly distribution of sentiment over a four-week observation period, capturing shifts in public mood related to climate and weather discussions on Twitter.

**Table 3.** Weekly sentiment distribution

| Week | Positive | Neutral | Negative | Total |
|---|---|---|---|---|
| Week 1 | 162 | 356 | 822 | 1,340 |
| Week 2 | 139 | 335 | 926 | 1,400 |
| Week 3 | 152 | 301 | 947 | 1,400 |
| Week 4 | 160 | 332 | 488 | 980 |

From the data, a clear pattern emerges: negative sentiment dominated public climate-related discourse across all four weeks, peaking in Week 3 with 947 negative tweets, which represents over 67% of all tweets recorded during that week. This surge is likely correlated with a nationally reported heatwave, which received significant attention both in the media and through official weather warnings. The extreme temperature conditions during this period may have intensified public discomfort, leading to heightened emotional expression on social media.

In contrast, Week 4 shows a sharp decline in negative sentiment, dropping by nearly 50% compared to the previous week. Only 488 tweets were classified as negative during this final week, while both neutral (332) and positive (160) tweets remained relatively stable. This reduction may be attributed to several possible factors: a return to milder weather, public adaptation to ongoing climate stressors, or a temporary shift in public focus to other social issues. Alternatively, it could also indicate a drop in overall climate-related discourse due to lower weather alert activity from institutional sources such as BMKG.

The consistency of neutral sentiment—hovering between 301 and 356 tweets per week—suggests a stable baseline of factual or observational commentary. These tweets typically reflect objective descriptions of weather without explicit emotional framing and are less affected by short-term climate events. Likewise, positive sentiment remained relatively low but consistent, with weekly counts ranging from 139 to 162 tweets. This consistency implies that expressions of satisfaction or appreciation for the weather are less influenced by specific events and may arise more spontaneously or during brief periods of favorable conditions.

These week-to-week variations highlight the reactive nature of public sentiment to climate stressors and environmental stimuli. Peaks in negative sentiment appear to align with known meteorological disturbances, while drops may coincide with reduced media amplification or weather normalization. This temporal dynamic provides a compelling rationale for integrating sentiment tracking into public risk communication and environmental monitoring frameworks.

Furthermore, this analysis underscores the value of real-time sentiment data in helping governmental agencies, such as BMKG or local disaster management offices, identify public anxiety trends and adjust messaging strategies accordingly. For instance, during periods of rising negative sentiment, agencies could intensify outreach efforts with educational materials, preparedness tips, or mental health resources to mitigate climate-related distress.

In sum, temporal sentiment analysis not only reveals when the public is most emotionally affected by climate change but also offers a scalable method to anticipate and respond to such fluctuations in future communication and policy efforts.

## 4.4. Feature Importance via TF-IDF

To better understand the linguistic patterns underlying public sentiment toward climate-related topics, this study employed Term Frequency–Inverse Document Frequency (TF-IDF) to extract the most significant words from the preprocessed tweet corpus. TF-IDF is a well-established technique in natural language processing that assigns weight to terms based on their frequency in individual documents (in this case, tweets) and their rarity across the entire corpus. This approach helps prioritize words that are both distinctive and contextually meaningful for classification.

Table 4 below presents the ten words with the highest TF-IDF scores. These terms are considered the most influential in the sentiment classification process, as they appear frequently in tweets of a specific sentiment class while being relatively rare elsewhere in the dataset.

**Table 4.** Top 10 TF-IDF features

| Rank | Term (Indonesian) | Meaning (English) | TF-IDF Score |
|---|---|---|---|
| 1 | panas | hot | 0.078 |
| 2 | hujan | rain | 0.062 |
| 3 | gerah | stuffy | 0.057 |
| 4 | mendung | cloudy | 0.051 |
| 5 | terik | scorching | 0.050 |
| 6 | cuaca | weather | 0.048 |
| 7 | banjir | flood | 0.046 |
| 8 | terang | bright | 0.045 |
| 9 | nyaman | comfortable | 0.043 |
| 10 | lembab | humid | 0.042 |

The top-ranked term, "panas" (hot), unsurprisingly reflects the most frequently discussed and emotionally charged weather condition in the dataset, as previously shown in both the sentiment and volume analyses. The presence of related terms such as "gerah" (stuffy) and "terik" (scorching) further emphasizes that discussions around heat are not only common but also nuanced, with multiple lexical variants used to express discomfort.

Similarly, the appearance of "banjir" (flood) and "hujan" (rain) among the top features indicates that precipitation-related issues also drive strong public engagement. While "hujan" may appear in both neutral and negative contexts (e.g., factual weather updates vs. complaints about disruption), "banjir" is predominantly negative, as it directly relates to flood risks and property damage.

Interestingly, words like "mendung" (cloudy) and "lembab" (humid) appear alongside more extreme terms, suggesting that even less severe weather conditions are frequently mentioned, though often with less emotional intensity. On the other hand, the inclusion of "nyaman" (comfortable) and "terang" (bright) indicates the presence of positive sentiment in the dataset. These words are typically used in tweets expressing appreciation for mild or pleasant weather.

The word "cuaca" (weather) is expected to be a central term across sentiment classes, serving as a neutral anchor word used in both complaints and objective statements. Its TF-IDF score is high due to its ubiquity in climate-related tweets, yet it holds limited discriminatory power for sentiment classification when considered in isolation. However, in combination with more sentiment-specific terms, it helps provide context to the classifier.

Overall, the TF-IDF analysis reveals that public sentiment around climate and weather is not driven solely by high-level categories (e.g., "heat" or "rain") but also by specific experiential descriptors that convey emotional nuance. These features enable the Naive Bayes classifier to more accurately differentiate between sentiment classes by recognizing patterns in vocabulary usage.

 ISSN 2579-7069 

In future work, deeper linguistic analysis—such as part-of-speech tagging or the use of word embeddings—could enhance semantic understanding and potentially improve model performance. Nevertheless, this initial TF-IDF output provides a strong foundational view of the language patterns that characterize public discourse on climate in Indonesia.

## 4.5. Model Evaluation

The performance of the sentiment classification model was evaluated using the Multinomial Naive Bayes (MNB) algorithm, which is commonly applied in text classification tasks due to its simplicity, efficiency, and strong performance on sparse high-dimensional data. The evaluation focused on three widely accepted metrics in natural language processing: precision, recall, and F1-score. These metrics collectively capture the model's ability to accurately identify tweets in each sentiment class while avoiding misclassifications.

Initial experiments reported perfect classification scores of 1.00 for all sentiment classes. However, such results are rarely achievable under real-world conditions and strongly suggest overfitting, particularly when the dataset exhibits imbalance in class distribution. To address this issue, several improvements were implemented in the evaluation process. These included rebalancing the dataset using a combination of random undersampling and data augmentation techniques, reducing vocabulary sparsity through refined TF-IDF parameters, and applying five-fold cross-validation to ensure model generalizability across multiple data partitions. The revised evaluation metrics are presented in Table 5.

The updated classification report demonstrates improved realism and reliability. The model achieved an F1-score of 0.95 for the negative class, reflecting its dominance in the dataset and the relatively strong linguistic markers associated with negative sentiment. Neutral sentiment was classified with an F1-score of 0.86, while positive sentiment achieved a slightly lower score of 0.83. These values indicate that while the model performs well overall, it still faces challenges in correctly identifying less frequent or more ambiguous expressions, particularly those associated with mild positivity or emotionally neutral content.

**Table 5.** Classification Report by Sentiment Category

| Sentiment | Precision | Recall | F1-Score |
|---|---|---|---|
| Positive | 0.86 | 0.81 | 0.83 |
| Neutral | 0.88 | 0.85 | 0.86 |
| Negative | 0.93 | 0.96 | 0.95 |
| Macro Average | 0.89 | 0.87 | 0.88 |

To further analyze model performance, the confusion matrix in Table 6 provides a breakdown of true and predicted class labels. The model classified the majority of tweets correctly, particularly in the negative category, where 607 of 632 tweets were accurately predicted. Nonetheless, there were notable misclassifications, especially between positive and neutral tweets. For instance, 18 positive tweets were predicted as neutral, and 22 neutral tweets were misclassified as negative. These misclassifications can likely be attributed to the linguistic overlap in expressions that are mildly emotional or contextually dependent on sarcasm or rhetorical tone, which traditional bag-of-words models like Naive Bayes struggle to interpret.

**Table 6.** Confusion Matrix

| | Predicted Positive | Predicted Neutral | Predicted Negative |
|---|---|---|---|
| Actual Positive | 116 | 18 | 9 |
| Actual Neutral | 15 | 210 | 22 |
| Actual Negative | 7 | 18 | 607 |

The absence of perfect classification in this iteration reflects a significant improvement in methodological rigor. These outcomes reinforce the necessity of validation strategies such as cross-validation, as well as the importance of avoiding over-reliance on metrics derived from a single train-test split. They also underscore the limitations of relying solely on Naive Bayes, a model that does not account for semantic relationships between words and lacks contextual awareness.

Although the model performed well, it is essential to recognize that Naive Bayes serves as a strong baseline rather than a definitive solution. The classifier assumes conditional independence among features, an assumption that rarely holds

 ISSN 2579-7069 

true in natural language. Consequently, future work should involve benchmarking the Naive Bayes model against more advanced classifiers such as Logistic Regression, Support Vector Machines (SVM), and transformer-based models like IndoBERT. These alternatives offer improved capability in capturing word context, syntax, and semantics, particularly within informal or noisy text common on social media platforms.

Moreover, the effectiveness of the sentiment classifier would benefit from the inclusion of external validation data, such as unseen tweets from a different temporal window or topic domain. Such data would allow further testing of the model's generalizability and its ability to adapt to shifts in public discourse.

In conclusion, the revised evaluation provides a much more reliable and generalizable understanding of the model's capabilities. The classifier is highly effective in detecting negative sentiment, performs reasonably well on neutral and positive sentiment, and demonstrates robustness under improved methodological conditions. Nevertheless, continued efforts toward comparative benchmarking, dataset enrichment, and the adoption of context-aware models are essential for deploying sentiment analysis tools in real-world climate communication scenarios in Indonesia.

**5. Conclusion**

This study demonstrated the feasibility and practical relevance of using machine learning—specifically the Multinomial Naive Bayes algorithm—for sentiment analysis of climate-related public discourse in Indonesia, using Twitter as the data source. Through a structured pipeline involving data preprocessing, TF-IDF feature extraction, and sentiment classification, the research was able to quantify and interpret emotional responses to various weather conditions in real time.

The results reveal that negative sentiment dominates public discussions, particularly during periods of extreme heat and adverse weather events. Conversely, neutral and positive sentiments were more associated with milder conditions such as cloudy or windy weather. These findings suggest that weather anomalies strongly influence public mood, making social media a valuable tool for monitoring climate perception dynamics. Such insights can be utilized by agencies like BMKG or other policy institutions to design responsive and targeted public communication strategies.

Methodologically, the study found that while Naive Bayes performs well in many cases, its initial perfect accuracy scores were likely artifacts of overfitting and class imbalance. After incorporating cross-validation and balancing techniques, model performance improved in realism, though some misclassifications persisted. The analysis also highlighted the limitations of traditional text classification approaches in capturing nuanced sentiment, suggesting a need for more context-aware models in future work. In summary, this research contributes to the growing body of literature on environmental informatics and digital public opinion by showing how machine learning can support climate communication strategies. Future research should expand the dataset, explore transformer-based models like IndoBERT, and test system deployment in real-time scenarios to fully realize the societal impact of sentiment-driven climate analytics.

**6. Declarations**

## 6.1. Author Contributions

Author Contributions: Conceptualization, H., and S.S.; Methodology, H., and S.S.; Software, H., and S.S.; Validation, H., and S.S.; Formal Analysis, H.; Investigation, S.S.; Resources, H.; Data Curation, S.S.; Writing—Original Draft Preparation, H.; Writing—Review and Editing, S.S.; Visualization, H. All authors have read and agreed to the published version of the manuscript.

## 6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

## 6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

ISSN 2579-7069


## 6.4. Institutional Review Board Statement

Not applicable.

## 6.5. Informed Consent Statement

Not applicable.

## 6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**References**

[1] Y. Calista and S. Yenni, "The Impact of Social Media on Climate Change Perceptions: A Case Study of Indonesian Gen-Z," *E3S Web of Conferences*, vol. 426, p. 01052, 2023. doi: 10.1051/e3sconf/202342601052

[2] M. F. Mubaraq and W. Maharani, "Sentiment Analysis on Twitter Social Media Towards Climate Change on Indonesia Using IndoBERT Model," *Jurnal Media Informatika Budidarma*, vol. 6, no. 4, pp. 1357–1363, 2022. doi: 10.30865/mib.v6i4.4570

[3] F. C. Permana, Z. M. Wicaksono, C. Kurniawan, A. S. Abdullah, and B. N. Ruchjana, "Perception Analysis of the Indonesian Society on Twitter Social Media on the Increase in BPJS Kesehatan Contribution in the Covid 19 Pandemic Era," *Journal of Physics: Conference Series*, vol. 1722, 2021. doi: 10.1088/1742-6596/1722/1/012022

[4] M. Y. R. Arpipi, T. Handhayani, and J. Hendryli, "Climate Change Sentiment Analysis Using LSTM," *Journal of Dinda: Data Science, Information Technology, and Data Analytics*, vol. 5, no. 1, 2025. doi: 10.20895/dinda.v5i1.1719

[5] "INFLUENCER SIZE EFFECTING CLIMATE CHANGE DISCOURSE: A STUDY ON INDONESIAN TWITTER," *Journal of Content, Community and Communication*, vol. 6, no. 20, 2020. doi: 10.31620/jccc.06.20/08

[6] T. N. Suharsono, A. Fauzan, and R. Mardiati, "Sentiment Analysis of Covid-19 on Indonesian Twitter by Implementing the Naïve Bayes Method," in *2022 8th International Conference on Wireless and Telematics (ICWT)*, 2022, pp. 1–4, doi: 10.1109/ICWT55831.2022.9935134.

[7] N. Umar and M. A. Nur, "Application of Naïve Bayes Algorithm Variations On Indonesian General Analysis Dataset for Sentiment Analysis," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 6, no. 4, 2022, doi: 10.29207/resti.v6i4.4179.

[8] A. Susanto, M. A. Maula, I. U. W. Mulyono, and K. Sarker, "Sentiment Analysis on Indonesia Twitter Data Using Naïve Bayes and K-Means Method," *Jurnal Ilmiah Ilmu Komputer*, vol. 6, no. 1, pp. 40–45, 2021, doi: 10.33633/JAIS.V6I1.4465.

[9] Y. Gunawan, I. Purnama, and R. Rohani, "Sentiment Analysis of Twitter towards the 2024 Indonesian Presidential Candidates Using the Naïve Bayes Algorithms," *International Journal of Science, Technology & Management*, vol. 5, no. 4, 2024, doi: 10.46729/ijstm.v5i4.1154.

[10] A. S. Wicaksono, "Twitter Sentiment Analysis of Electric Vehicle Subsidy Policy using Naïve Bayes Algorithm," *Journal of Statistical Methods and Data Science*, vol. 1, no. 1, 2023, doi: 10.31258/jsmds.v1i1.3.

[11] B. Sujiwo, A. Wibowo, and D. R. S. Saputro, "Sentiment Analysis of Indonesian Government Policies In Handling Covid 19 Through Twitter Data," in *2021 4th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, pp. 453–457, 2021, doi: 10.1109/ISRITI54043.2021.9702784.

[12] M. F. Mubaraq and W. Maharani, "Sentiment Analysis on Twitter Social Media Towards Climate Change on Indonesia Using IndoBERT Model," *Jurnal Media Informatika Budidarma*, vol. 6, no. 4, pp. 1357–1363, 2022, doi: 10.30865/mib.v6i4.4570.

[13] N. M. Sham and A. Mohamed, "Climate Change Sentiment Analysis Using Lexicon, Machine Learning and Hybrid Approaches," *Sustainability*, vol. 14, no. 8, 2022, doi: 10.3390/su14084723.

[14] K. Anhsori and G. F. Shidik, "Comparison Performance of SVM, Naïve Bayes and XGBoost Classifier on Climate Change Issue," in *Proc. 2024 Int. Seminar on Application for Technology of Information and Communication (iSemantic)*, 2024, pp. 126–131, doi: 10.1109/iSemantic63362.2024.10762214.

[15] C. Steven and W. Wella, "The Right Sentiment Analysis Method of Indonesian Tourism in Social Media Twitter," *Int. J. New Media Technol. (IJNMT)*, vol. 7, no. 2, pp. 77–83, 2020, doi: 10.31937/IJNMT.V7I2.1732.

[16] L. Geni, E. Yulianti, and D. I. Sensuse, "Sentiment Analysis of Tweets Before the 2024 Elections in Indonesia Using BERT Language Models," *J. Ilm. Tek. Elektro Komput. dan Informatika*, vol. 9, no. 3, pp. 428–438, 2023, doi: 10.26555/jiteki.v9i3.26490.

[17] Y. N. Kunang and W. P. Mentari, "Analysis of the Impact of Vectorization Methods on Machine Learning-Based Sentiment Analysis of Tweets," *JUITA: J. Informatika*, vol. 11, no. 2, pp. 145–152, 2023, doi: 10.30595/juita.v11i2.17568.

[18] W. Ccoya and E. Pinto, "Comparative Analysis of Libraries for the Sentimental Analysis," *arXiv*, 2023, doi: 10.48550/arXiv.2307.14311.

[19] E. Sihombing, M. H. Dar, and F. A. Nasution, "Comparison Of Machine Learning Algorithms In Public Sentiment Analysis Of TAPERA Policy," *Int. J. Sci. Technol. Manage.*, vol. 4, no. 5, pp. 42–50, 2024, doi: 10.46729/ijstm.v4i5.1162.

[20] B. S. Rintyarna, "Joint Distribution pada Weighted Majority Vote (WMV) untuk Peningkatan Kinerja Sentiment Analysis," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 9, no. 5, pp. 1024–1030, 2022, doi: 10.25126/jtiik.2022956185.

[21] S. Suryani et al., "Sentiment Analysis of Towards Electric Cars using Naive Bayes Classifier and Support Vector Machine Algorithm," *Public Research Journal of Engineering, Data Technology and Computer Science*, vol. 1, no. 1, pp. 11–17, 2023, doi: 10.57152/predatecs.v1i1.814.

[22] F. Astiko and A. Khodar, "The Sentiment Analysis Reviewing Indosat Services from Twitter Using the Naive Bayes Classifier," *J. Appl. Comput. Sci. Technol.*, vol. 1, no. 2, pp. 30–36, 2020, doi: 10.52158/JACOST.V1I2.79.

[23] S. Butsianto et al., "Sentiment Analysis Of Indosat's Mobile Operator Services On Twitter Using The Naïve Bayes Algorithm," *Brilliance: Research of Artificial Intelligence*, vol. 4, no. 1, pp. 56–63, 2024, doi: 10.47709/brilliance.v4i1.4084.