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PERFORMANCE ANALYSIS OF MACHINE LEARNING FOR NATURAL DISASTER AID DISTRIBUTION SENTIMENT CLASSIFICATION

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Abstract

The distribution of post-natural disaster aid plays a crucial role in maintaining public trust and supporting affected communities in Indonesia. However, public criticisms regarding uneven or delayed distribution frequently emerge on social media platforms such as X (Twitter). This study aims to evaluate and compare the performance of six supervised machine learning algorithms are Support Vector Machine (SVM), Neural Network, K-Nearest Neighbors (KNN), Decision Trees, Random Forest, and Naive Bayes in classifying public sentiment toward post-disaster aid distribution. The dataset was collected via social media scraping from platform X, consisting of 998 data points. Prior to model implementation, the dataset underwent a preprocessing stage comprising case folding, cleansing, tokenization, stemming, and stopword removal (filtering), followed by Term Frequency-Inverse Document Frequency (TF-IDF) feature extraction. Subsequently, the data were trained using the six aforementioned methods. The experimental results reveal that SVM achieved the highest classification accuracy of 84.0%, closely followed by Neural Network at 83.0%. Meanwhile, KNN, Decision Trees, Random Forest, and Naive Bayes obtained accuracy scores of 79.0%, 74.0%, 73.0%, and 71.0%, respectively. Therefore, it can be concluded that the SVM algorithm performs sentiment classification very effectively on this disaster aid dataset.

Keywords: *Disaster Aid, Machine Learning, Platform X, Sentiment Analysis, Classification*

Abstrak

Penyaluran bantuan pascabencana alam memegang peranan penting dalam menjaga kepercayaan publik serta mendukung pemulihan masyarakat terdampak di Indonesia. Namun, kritik masyarakat terkait ketidakmerataan atau keterlambatan penyaluran sering kali muncul di platform media sosial X (Twitter). Penelitian ini bertujuan untuk mengevaluasi dan membandingkan performa enam algoritma pembelajaran mesin berbasis supervised learning, yaitu Support Vector Machine (SVM), Neural Network, K-Nearest Neighbors (KNN), Decision Trees, Random Forest, dan Naive Bayes dalam mengklasifikasikan sentimen publik terhadap penyaluran bantuan bencana. Dataset yang digunakan diperoleh melalui teknik scraping media sosial X dengan total 998 data. Sebelum diterapkan pada model, dataset terlebih dahulu melalui tahap prapemrosesan yang meliputi case folding, cleansing, tokenizing, stemming, dan stopword removal (filtering), dilanjutkan dengan ekstraksi fitur Term Frequency-Inverse Document Frequency (TF-IDF).

Selanjutnya, data dilatih menggunakan keenam metode tersebut. Hasil penelitian menunjukkan bahwa SVM mencapai akurasi klasifikasi tertinggi sebesar 84,0%, disusul oleh Neural Network sebesar 83,0%. Sementara itu, KNN, Decision Trees, Random Forest, dan Naive Bayes masing-masing memperoleh akurasi sebesar 79,0%, 74,0%, 73,0%, dan 71,0%. Oleh karena itu, dapat disimpulkan bahwa algoritma SVM mampu melakukan klasifikasi sentimen dengan sangat baik pada data penyaluran bantuan bencana ini.

Kata Kunci: *Disaster Aid, Machine Learning, Platform X, Sentiment Analysis, Classification*

1. Introduction

Indonesia is recognized as one of the countries with the highest natural disaster risk globally [1], [2]. Geographically situated along active tectonic plate intersections and possessing diverse topographic conditions, the archipelago is highly vulnerable to earthquakes, floods, landslides, and other hydrometeorological disasters [1], [2]. Global disaster risk assessments consistently rank Indonesia among the few countries with the highest disaster exposure worldwide [1], [2]. When disasters strike, the distribution of post-disaster aid to affected populations represents a critical aspect of emergency response and recovery efforts [3]. The speed, accuracy of targeting, and equity of aid distribution significantly influence public perception and trust in government authorities and humanitarian organizations [3]. Concurrently, social media platforms such as X (formerly Twitter) have emerged as primary public spaces where citizens openly express real-time opinions, including both appreciation and grievances regarding disaster management [3], [4].

The massive volume of public commentary on social media poses substantial challenges for manual monitoring, necessitating computational approaches capable of processing large-scale text data [4]. Sentiment analysis using machine learning techniques offers an effective solution by identifying emotional tone in written text and categorizing public expressions into positive, neutral, or negative classes [5]. Through automated digital platform analysis, overall trends in public perception can be mapped in a rapid, measurable, and optimal manner [7]. Previous disaster-related studies have demonstrated the utility of text classification, such as applying Naïve Bayes with N-Gram features to evaluate post-disaster sentiment [7]. Across broader domains, machine learning sentiment analysis has been widely implemented in movie review evaluations [6], data security perception studies [8], public health monitoring [9], [10], and public policy evaluations regarding vaccination programs [11]. Among various supervised architectures, Support Vector Machine (SVM) and Random Forest (RF) have consistently emerged as two highly effective and competitive models for text classification tasks [4], [11], [12].

From an algorithmic standpoint, evaluating different classification paradigms provides deeper insights into text data behavior. SVM constructs optimal hyperplanes in high-dimensional feature spaces, making it exceptionally robust when paired with Term Frequency-Inverse Document Frequency (TF-IDF) feature representations [4], [11]. In contrast, RF utilizes ensemble learning by aggregating decision trees to stabilize variance and prevent overfitting on noisy social media text [11], [12]. Furthermore, alternative architectures offer unique operational trade-offs: Multi-Layer Perceptron Neural Networks excel at modeling complex non-linear relations, K-Nearest Neighbors (KNN) relies on distance-based similarity metrics, Decision Trees (DT) provide interpretable

rule-based structures, and Naive Bayes (NB) delivers high computational efficiency through probabilistic modeling [7], [12].

Despite the growing body of literature on machine learning text classification, comprehensive benchmark studies comparing classical probabilistic, distance-based, tree-based, ensemble, margin-based, and neural architectures specifically within the context of Indonesian post-disaster aid distribution remain essential. Most domain-specific studies focus either on single classifiers or restrict comparisons to limited model subsets [7], [11], [12]. To address this gap, this study analyzes public sentiment on platform X regarding the effectiveness, targeting accuracy, and overall perception of post-disaster aid distribution in Indonesia. A comparative performance evaluation is conducted across six machine learning algorithms: Support Vector Machine (SVM), Random Forest (RF), Neural Network, K-Nearest Neighbors (KNN), Decision Trees (DT), and Naive Bayes (NB). Using a dataset of 998 Indonesian tweets processed through standard text preprocessing and TF-IDF feature extraction, the findings aim to provide objective insights into public sentiment trends to assist governing bodies in improving disaster relief logistics.

2. Method

In this study, an analysis of public perception of the post-disaster aid distribution in Indonesia was conducted using sentiment analysis based on machine learning methods. The overall execution flow is summarized in Figure 1. The first step involves data collection, where this study uses text data collected from social media platform X that detail citizen feedback, grievances, and perceptions regarding government post-disaster relief efforts. After the data exploration process, relevant responses discussing aid distribution were filtered and collected, resulting in a total of 998 data points used for further analysis.

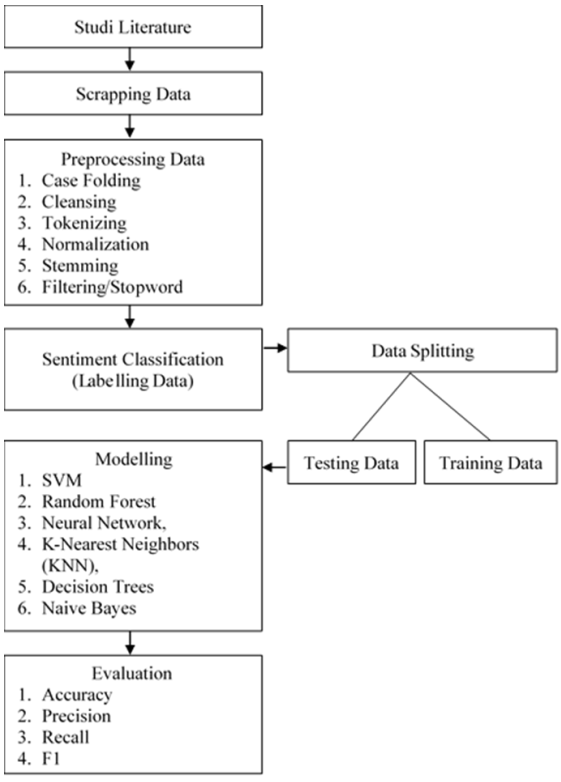

Figure. 1. Workflow Diagram Method

The evaluation stage was executed to measure each model's capacity to identify underlying textual patterns within the corpus. Before training, the preprocessed text was partitioned into training and testing subsets, followed by feature extraction using the Term Frequency-Inverse Document Frequency (TF-IDF) technique to convert textual entries into numerical vector representations. This conversion is necessary to enable effective model training across six selected algorithms: Naïve Bayes, Support Vector Machine (SVM), Random Forest, Neural Network, K-Nearest Neighbors (KNN), and Decision Tree. The performance of the resulting models was then validated using a confusion matrix, with accuracy, precision, recall, and F1-score metrics as the main indicators in measuring the accuracy of the classification results.

A. Scraping Data

The dataset for this study was collected from social media platform X (formerly Twitter) using web scraping techniques. The gathered data consists of tweets in Indonesian, focusing on public reactions, opinions, and complaints regarding post-disaster aid distribution across various regions in Indonesia. Covering the period from January 2023 to May 2026. A total of 998 raw data entries were collected and saved in CSV format for subsequent analysis.

B. Pre-Processing Data

Text preprocessing is an essential phase designed to clean, structure, and prepare unstructured textual data for computational analysis. Within the Natural Language Processing (NLP) framework, preprocessing ensures that feature extraction yields high-quality representations, directly enhancing model stability and predictive accuracy during training and testing. In this research, six consecutive preprocessing steps were performed.

1. Case Folding

The initial preprocessing step is case folding, which aims to standardize the textual data by converting all characters to lowercase. This step is performed to maintain consistency in textual representations and minimize feature variations caused by uppercase and lowercase letter differences during subsequent processing steps.

TABLE 1 RESULT CASE FOLDING

Raw Text	Result Case Folding
Puan Maharani dorong penyaluran bantuan logistik dan layanan kesehatan segera sampai ke tangan warga terdampak gempa Sulawesi Utara. Mari kita kawal bersama! 🏢🏢 #puanmaharani #bbvipal5 #StarAcademy #Vina2026	puan maharani dorong penyaluran bantuan logistik dan layanan kesehatan segera sampai ke tangan warga terdampak gempa sulawesi utara. mari kita kawal bersama! 🏢🏢 #puanmaharani #bbvipal5 #staracademy #vina2026

2. Cleansing

Data cleansing is carried out to eliminate non-informative elements from the corpus. This involves removing usernames (@user), retweet indicators, hashtags (#), single isolated characters, numerical digits, web URLs, punctuation marks, and extraneous spaces. In addition, emojis and emoticons are stripped to refine the quality of the dataset for further textual analysis.

TABLE 2 RESULT CLEANSING

Raw Text	Result Cleansing
puan maharani dorong penyaluran bantuan logistik dan layanan kesehatan segera sampai ke tangan warga terdampak gempa sulawesi utara. mari kita kawal bersama!  #puanmaharani #bbvipal5 #staracademy #vina2026	puan maharani dorong penyaluran bantuan logistik dan layanan kesehatan segera sampai ke tangan warga terdampak gempa sulawesi utara. mari kita kawal bersama

3. Tokenizing

Tokenization is performed to segment continuous sentence strings into distinct individual words (tokens). These tokens represent the fundamental units of meaning in text processing and serve as the foundational elements for feature construction.

TABLE 3 RESULT TOKENIZING

Raw Text	Result Tokenizing
puan maharani dorong penyaluran bantuan logistik dan layanan kesehatan segera sampai ke tangan warga terdampak gempa sulawesi utara. mari kita kawal bersama	['puan', 'maharani', 'dorong', 'penyaluran', 'bantuan', 'logistik', 'dan', 'layanan', 'kesehatan', 'segera', 'sampai', 'ke', 'tangan', 'warga', 'terdampak', 'gempa', 'sulawesi', 'utara', 'mari', 'kita', 'kawal', 'bersama']

4. Normalization (Slang Word Conversion)

Text normalization is applied to resolve non-standard linguistic variations by converting informal slang, typos, and colloquial Indonesian words into their standard formal dictionary equivalents using a normalization dictionary. Furthermore, negation terms are contextualized to allow the classification models to accurately preserve negative semantic intent.

5. Stemming

Stemming is applied to strip affixes (prefixes, infixes, and suffixes) from inflected words, reducing them to their core base root forms. This process ensures that different morphological variations of a word are mapped to a single unified term during feature vectorization.

TABLE 4 RESULT STEMMING

Raw Text	Result Stemming
['puan', 'maharani', 'dorong', 'penyaluran', 'bantuan', 'logistik', 'dan', 'layanan', 'kesehatan', 'segera', 'sampai', 'ke', 'tangan', 'warga', 'terdampak', 'gempa', 'sulawesi', 'utara', 'mari', 'kita', 'kawal', 'bersama']	['puan', 'maharani', 'dorong', 'penyaluran', 'bantuan', 'logistik', 'dan', 'layanan', 'sehat', 'segera', 'sampai', 'ke', 'tangan', 'warga', 'dampak', 'gempa', 'sulawesi', 'utara', 'mari', 'kita', 'kawal', 'bersama']

6. Filtering (Stopword Removal)

Stopword filtering is executed to remove extremely frequent non-semantic words—such as conjunctions, pronouns, and prepositions—that do not contribute meaningful domain-specific context to the sentiment classification process.

TABLE 5 RESULT FILTERING (STOPWORD REMOVAL)

Raw Text	Result Filtering (Stopword Removal)
['puan', 'maharani', 'dorong', 'penyaluran', 'bantuan', 'logistik', 'dan', 'layanan', 'sehat', 'segera', 'sampai', 'ke', 'tangan', 'warga', 'dampak', 'gempa', 'sulawesi', 'utara', 'mari', 'kita', 'kawal', 'bersama']	['puan', 'maharani', 'dorong', 'penyaluran', 'bantuan', 'logistik', 'layanan', 'sehat', 'segera', 'tangan', 'warga', 'dampak', 'gempa', 'sulawesi', 'utara', 'kawal', 'bersama']

C. Sentiment Classification

Upon completing the preprocessing pipeline, a total of 998 processed data samples were prepared for analysis. The subsequent phase involved sentiment tagging to assign ground-truth target labels required for supervised machine learning training. Public opinions were classified into positive and negative sentiment categories. This labeling process provides the necessary contextual targets for the algorithms to learn predictive patterns regarding post-disaster aid perception. Ground-truth labels were assigned automatically using a lexicon-based approach with the InSet (Indonesian Sentiment Lexicon) positive and negative word lists [13]. For each preprocessed (stemmed) tweet, the number of negative lexicon words was subtracted from the number of positive lexicon words to obtain a sentiment score. Tweets with a score greater than zero were labeled Positive, whereas tweets with a score of zero or below, including those containing no matching lexicon words, were labeled Negative. Because no manual annotation was involved, inter-annotator agreement (Cohen's Kappa) is not applicable.

TABLE 6 DISTRIBUTION DATA BASED ON SENTIMENT CLASSIFICATION

Sentiment Class	Amount	Percentage (%)
Negative	675	67,64%
Positive	323	32,36%

D. Data Splitting

Data splitting is conducted to evaluate the generalizability of the machine learning algorithms by partitioning the dataset into distinct training and testing subsets. In this study, the corpus was divided using an 90:10 ratio, where 89,98% of the samples (898 entries) were assigned to train the models and the remaining 10,02% (100 entries) were set aside for testing. This proportion was chosen to ensure the classifiers have sufficient training data to learn complex features while maintaining a statistically robust holdout test set for evaluation. Stratified sampling was applied to preserve class distribution balance across both subsets.

E. Modelling

Prior to model training, the preprocessed textual data undergoes feature extraction using the TF-IDF (Term Frequency-Inverse Document Frequency) Vectorizer to convert unstructured text into high-dimensional numerical vectors. The TF-IDF mechanism integrates two main components: Term Frequency (TF), which measures word density in a document, and Inverse Document Frequency (IDF), which suppresses the weight of common terms occurring indiscriminately across the entire dataset. Subsequently, sentiment classification is performed by training six distinct supervised machine learning algorithms: Naïve Bayes as a probabilistic approach based on Bayes' theorem assuming feature independence, Support Vector Machine (SVM) which constructs optimal hyperplanes to maximize class margins, Random Forest as an ensemble technique combining multiple decision trees to stabilize variance, Neural Network (Multi-Layer Perceptron) to capture non-linear feature interactions, K-Nearest Neighbors (KNN) based

on distance similarity metrics, and Decision Tree which partitions feature space using rule-based decision nodes. Each model learns predictive patterns from the training vectors to classify post-disaster aid sentiment effectively.

F. Evaluation

The predictive performance of each trained model was evaluated on the test set using a confusion matrix. This matrix provides a statistical summary comparing predicted class assignments against actual ground-truth labels. Model evaluation relied on four core indicators: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). From these values, standard performance metrics namely Accuracy, Precision, Recall, and F1-Score were computed to benchmark the six algorithms and identify the optimal classifier for post-disaster aid sentiment analysis.

3. Result and Analysis

Sentiment analysis on public commentary regarding post-disaster aid in Indonesia was conducted using six supervised machine learning models to evaluate public perception and model efficacy. Following text preprocessing and TF-IDF feature extraction, the complete dataset comprising 998 tweets was analyzed for class distribution, as illustrated in Figure 2. The class distribution reveals a notable imbalance, with negative sentiment dominating the corpus at 67.64% (675 tweets) compared to positive sentiment at 32.36% (323 tweets). This distribution underscores that social media commentary during disaster recovery is heavily focused on critical grievances, operational challenges, and urgent calls for emergency relief.

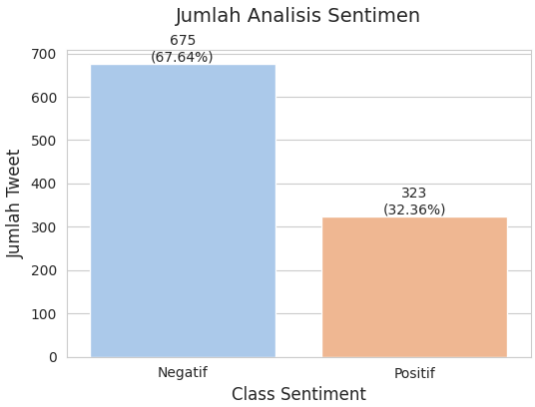

Figure. 2. Sentiment Distribution

Lexical analysis via word clouds further elucidates the primary linguistic patterns within these sentiment categories. As shown in Figure 3, negative discourse is heavily populated by urgent operational terms such as “bantu”, “salur”, “bencana”, “dampak”, “korban”, “masyarakat”, “pemerintah”, and ‘tanggulang” alongside regional descriptors like “sumatera”, “aceh”, and banjir. This indicates that public dissatisfaction primarily stems from flood relief logistics and delivery delays.

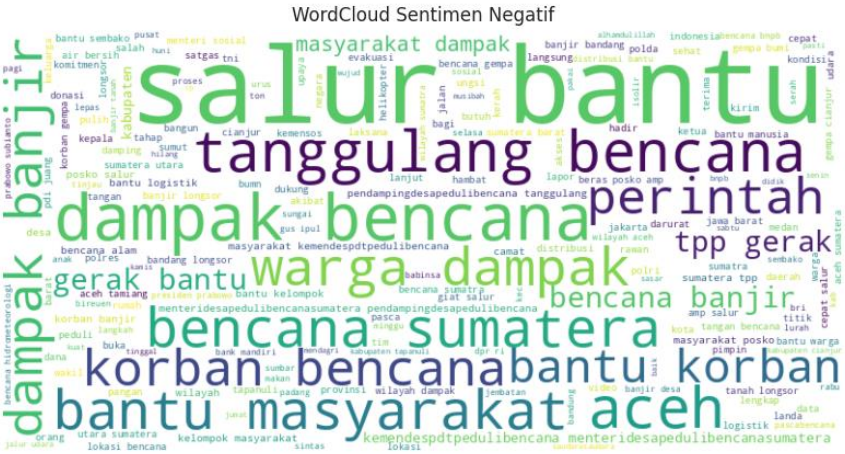

Figure. 3. Negative Sentiment Word Cloud

Conversely, as depicted in Figure 4, positive discussions feature constructive and appreciative terms including “salur”, “bantu”, “korban”, “cepat”, “langsung”, “donasi”, “pulih”, and “terima kasih”, reflecting public recognition of swift aid delivery, community solidarity, and active rehabilitation efforts.

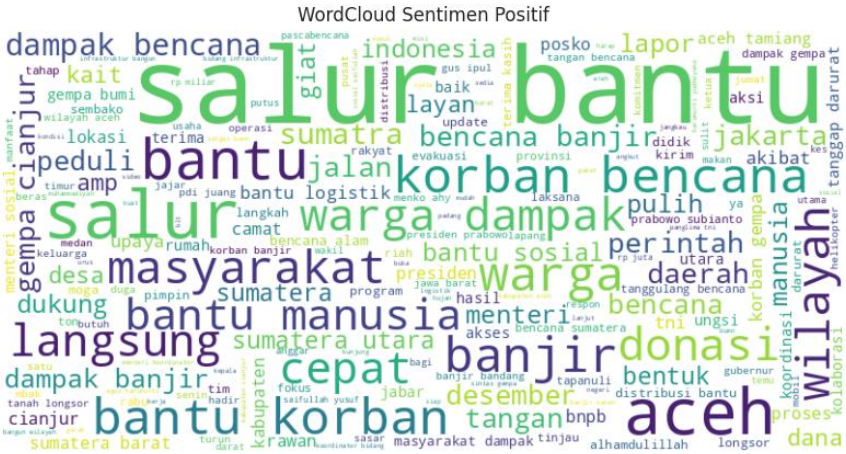

Figure. 4. Positive Sentiment Word Cloud

After analyzing the dataset, the next step is the modeling process to build a model that can perform sentiment analysis on the processed dataset. During modeling, the model is trained on training data so it can learn and recognize patterns in the dataset. After learning these patterns, testing is carried out using test data, and the sentiment evaluation results for each class are presented in Table 7.

TABLE 7 PERFORMANCE MODEL BASED ON SENTIMENT

Model	Class	Precision	Recall	F1-Score
SVM	Positive	0,767	0,719	0,742
	Negative	0,871	0,897	0,884
Accuracy				0,840
Neural Network	Positive	0,759	0,688	0,721
	Negative	0,859	0,897	0,878
Accuracy				0,830
KNN	Positive	0,789	0,469	0,588
	Negative	0,790	0,941	0,859
Accuracy				0,790

Model	Class	Precision	Recall	F1-Score
Decision Trees	Positive	0,575	0,719	0,639
	Negative	0,850	0,750	0,797
Accuracy				0,740
Random Forest	Positive	0,667	0,312	0,426
	Negative	0,741	0,926	0,824
Accuracy				0,730
Naïve Bayes	Positive	0,552	0,500	0,525
	Negative	0,775	0,809	0,791
Accuracy				0,710

The quantitative evaluation of classification performance presented in Table 7 reveals clear empirical distinctions among the six algorithms on the test set. Support Vector Machine (SVM) achieved the highest performance with an overall accuracy of 84.0% (F1-score Negative = 0.884; Positive = 0.742), closely followed by Neural Network (Multi-Layer Perceptron) at 83.0% accuracy (F1-score Negative = 0.878; Positive = 0.721). K-Nearest Neighbors (KNN) reached an accuracy of 79.0%, whereas Decision Trees, Random Forest, and Naïve Bayes recorded lower accuracies of 74.0%, 73.0%, and 71.0%, respectively. In-depth comparative analysis indicates that margin-maximizing classifiers like SVM and multi-layer non-linear transformations like Neural Networks are significantly more robust when handling high-dimensional, sparse TF-IDF text features. These models maintain balanced predictive capabilities across both majority (Negative) and minority (Positive) sentiment classes. In contrast, tree-based ensemble methods like Random Forest and probabilistic algorithms like Naïve Bayes exhibited severe degradation on minority class prediction, as evidenced by low positive class recall scores of 0.312 and 0.500. Distance-based KNN similarly biased its predictions toward the majority negative class (Recall = 0.941) while struggling on the positive class (Recall = 0.469; F1-score = 0.588). Consequently, linear kernel optimization (SVM) proves to be the most effective strategy for mitigating class imbalance and accurately classifying public disaster management sentiment.

4. Conclusion

This study evaluated six supervised machine learning algorithms to analyze public sentiment regarding post-disaster aid distribution in Indonesia using social media data from platform X. Analysis of the 998 preprocessed dataset revealed a notable class imbalance, where negative sentiment dominated at 67.64% (675 tweets) compared to positive sentiment at 32.36% (323 tweets). Lexical patterns showed that public grievances mainly revolved around flood logistics, damage, and aid delivery delays, whereas positive discussions reflected appreciation for rapid relief operations and community support. Among the evaluated algorithms, Support Vector Machine (SVM) achieved the highest classification performance with an accuracy of 84.0% (F1-score Negative = 0.884; Positive = 0.742), closely followed by the Neural Network model at 83.0%. In contrast, algorithms such as Random Forest (73.0%) and Naïve Bayes (71.0%) struggled with predicting the minority positive class. Overall, linear kernel optimization via SVM proved to be the most robust approach for handling high-dimensional text data and class imbalance in post-disaster public sentiment monitoring.

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