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Public Sentiment Analysis of the Affan Kurniawan Social Issue on X (Sosial Media): A Comparison of Naïve Bayes and SVM Algorithms

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ABSTRACT
Social media X is a fast-moving public arena where public opinions on social issues spread rapidly, including the Affan Kurniawan case. This study aims to (i) identify the sentiment distribution, (ii) compare Multinomial Naïve Bayes and linear SVM (LinearSVC) on the same dataset, and (iii) assess classification consistency under a uniform evaluation scheme. Indonesian-language posts were collected via keyword-based crawling and stored in a CSV file (affan_kurniawan.csv). After removing empty and duplicate texts, 10,624 raw records were reduced to 7,431 cleaned records collected between 28 August 2025 and 02 September 2025. Texts were preprocessed (normalization, tokenization, stopword removal, stemming) and automatically labeled into negative, neutral, and positive classes using a lexicon-based rule approach. The resulting distribution was 3,735 negative (50.26%), 2,301 neutral (30.96%), and 1,395 positive (18.77%). Features were represented using Bag-of-Words with CountVectorizer and evaluated using an 80:20 train–test split (5,944 training; 1,487 testing). SVM outperformed Naïve Bayes, achieving accuracy 0.826 vs 0.745 and macro F1-score 0.759 vs 0.579, indicating that SVM provides a stronger baseline for sentiment classification in this case study.

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1. INTRODUCTION

Social media X (formerly Twitter) has evolved into a digital public sphere that plays an important role in shaping public opinion on various social issues through rapid and large-scale text-based interactions [1]. X's real-time, open, and conversational nature makes it a relevant data source for examining public sentiment dynamics, although it also introduces challenges such as informal language, semantic ambiguity, and fast topic shifts [2]. The renaming of Twitter to X also has academic implications in digital communication studies, particularly regarding consistent source labeling in scholarly research [3]. In sentiment analysis, preprocessing quality is a crucial factor because normalizing informal text, tokenization, and stopword removal have been shown to significantly affect model performance on noisy, non-standard social media data [4]. Beyond preprocessing, systematic reviews indicate that the validity of social media sentiment analysis is also strongly influenced by data collection design, sampling strategies, and the selection of appropriate evaluation metrics; therefore, transparent methodological reporting is essential for replication and cross-study comparison [5]. Accordingly, selecting and refining stopword lists must be done carefully to reduce non-informative terms, since text preprocessing—including stopword removal—can affect feature representation and sentiment classification performance [4]. In addition to linguistic challenges, public discourse on X is often shaped by automated accounts and manipulative behaviors intended to amplify information diffusion and influence opinion; empirical studies report that about 20% of social media conversations about global events originate from bots, whose linguistic and interaction patterns differ from those of human users and may undermine authentic discourse [6]. Other research shows that automated accounts can strengthen echo chambers and spread misinformation, which in some situations manipulates public sentiment and reverses attitudes toward an issue [7]. These findings align with large-scale evidence highlighting bot–human linguistic differences, suggesting that bot presence can alter observed sentiment signals if not controlled during analysis [6]. Literature on stance detection in tweets further emphasizes that sentiment and stance are related but not identical concepts; therefore, this study focuses on sentiment polarity classification (positive, neutral, and negative) to avoid conflating results with support–opposition positioning, which requires different analytical approaches [8].

The Affan Kurniawan case is a social issue that triggered a surge of conversations on X, featuring diverse expressions of opinions, emotions, and judgments. The informal nature and high volume of such discourse make it difficult to capture public sentiment objectively without machine-learning-based text classification techniques [9]. In text classification, Naïve Bayes and Support Vector Machine (SVM) are widely used algorithms in sentiment analysis because they are effective in handling high-dimensional and sparse text data represented as word vectors. Naïve Bayes is commonly employed as a probabilistic baseline model due to its computational efficiency, simplicity, and robustness when applied to discrete word-frequency features, making it suitable for large-scale social media datasets. In contrast, SVM is a margin-based classifier that has been extensively reported to achieve strong performance on high-dimensional text data by maximizing class separation, particularly in situations where sentiment classes overlap within the feature space.

The selection of these two algorithms in this study is motivated by their complementary roles in sentiment classification research. Naïve Bayes provides an interpretable and efficient baseline model, while SVM represents a more discriminative approach capable of capturing more complex decision boundaries. By comparing Naïve Bayes and SVM under the same Bag-of-Words (BoW) feature representation and a uniform evaluation scheme, this study enables a fair and transparent assessment of probabilistic versus margin-based learning approaches for sentiment analysis on social media X data.

Bag-of-Words (BoW) feature representation with CountVectorizer is commonly used because it is simple, interpretable, and compatible with classical classifiers such as Naïve Bayes and SVM for modeling word-frequency patterns in text [10]. However, the performance of both algorithms can be influenced by feature representation choices, class distribution in the dataset, and the evaluation scheme employed [11]. For this reason, BoW is often positioned as an interpretable baseline, and evaluation studies on tweet data also suggest that feature representation and classifier selection substantially affect cross-domain performance outcomes [12].

This study aims to analyze public sentiment toward the Affan Kurniawan social issue on X while comparing the performance of Naïve Bayes and SVM for sentiment classification. The study focuses on identifying sentiment distribution, evaluating both algorithms on the same dataset, and assessing the consistency of classification results under a uniform evaluation scheme [13]. The scope is limited to public posts on X within a specific time window, with limitations including potential sampling bias, the presence of automated accounts, and non-standard language variation that is difficult for models to interpret. The contribution of this study is to provide empirical evidence on public sentiment dynamics surrounding a social issue on X and a comparative evaluation of two widely used sentiment classification algorithms, which is expected to enrich methodological discussions in social-media-based sentiment analysis and inform the development of more adaptive models in future research [14].

2. RESEARCH METHOD

This study employs a quantitative design with a computational–experimental approach to analyze public sentiment toward the Affan Kurniawan social issue on social media X. A machine-learning-based sentiment analysis approach is selected because it can process large-scale text data systematically and objectively to identify trends in public opinion on social media. Previous studies indicate that sentiment analysis on social media platforms is effective for understanding public responses to social issues and public policies [15]. Similar X-based sentiment analysis practices—using train–test splits and performance-metric evaluation—are also widely applied in related studies, including publications in the Indonesian Journal of Data and Science (IJODAS); therefore, this research design is consistent with methodological practices commonly used in social-media-based sentiment analysis research [16]. The research workflow is organized sequentially from data collection, preprocessing, and feature representation to modeling and performance evaluation, as illustrated in Figure 1, which presents the research flow.

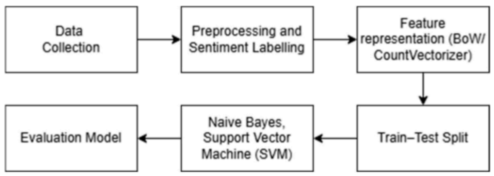

Figure 1.Research Flow

To ensure transparency and replicability, the study was conducted through the following sequential stages:

1) Data collection (crawling) and data storage: Public posts on social media X were collected using keywords relevant to the Affan Kurniawan case, restricted to Indonesian-language posts, and stored in CSV format for analysis [10], [17].
2) Initial data cleaning (raw dataset screening): Empty entries and duplicate posts (identical text content) were removed (dropna and drop_duplicates on the text column) to improve representativeness and reduce redundancy.
3) Text preprocessing (notebook output columns): Preprocessing was applied to reduce noise and standardize vocabulary before feature extraction, following the notebook column names:
    a. cleaning: remove URL, HTML tags, emojis, symbols/punctuation, and numbers, producing the 'cleaning' text.
    b. case_folding: convert all characters to lowercase, producing 'case_folding'.
    c. normalisasi: replace non-standard/slang words with standard Indonesian forms using a slang dictionary, producing 'normalisasi'.
    d. tokenize: split text into word tokens, producing 'tokenize'.
    e. stopword removal: remove Indonesian stopwords, producing 'stopword removal'.
    f. stemming_data: reduce words to their root forms using Sastrawi, producing 'stemming_data'.
4) Sentiment labeling (rule-/lexicon-based): Sentiment classes (negative, neutral, positive) were assigned after preprocessing using a rule-based lexicon approach. This automatic labeling may introduce label noise, which is treated as a study limitation [18].
5) Feature representation (BoW-CountVectorizer): The preprocessed texts were converted into numerical features using Bag-of-Words (BoW) with CountVectorizer, which is commonly used for comparing classical classifiers such as Naïve Bayes and SVM on social media text [19], [20].
6) Train-test split (80:20, stratified): The feature dataset was split into training and testing sets using an 80:20 stratified split (random_state=42) to preserve sentiment class proportions and ensure evaluation on unseen test data.

7) Modeling (MultinomialNB vs LinearSVC): Two classifiers were trained and compared on the same training data and feature representation: Multinomial Naïve Bayes and SVM (LinearSVC) [21], [22].
8) Performance evaluation (metrics + confusion matrices): Performance was measured on the test set using accuracy, precision, recall, and F1-score (macro and weighted averages) and analyzed with confusion matrices to inspect class-wise errors [23].

The research data consist of public posts from social media X obtained through automated data collection (crawling) using keywords relevant to the Affan Kurniawan case and restricted to Indonesian-language posts. The collected data are stored in CSV format and loaded into a dataframe for further analysis. In the initial stage, data cleaning is performed by removing empty entries and duplicate posts based on identical text content to ensure the dataset is more representative. The use of Twitter/X data as a source for sentiment analysis research has been widely adopted in prior studies because it can reflect public opinion in real time and at large scale [10]. In addition, changes in data-access policies on the Twitter/X platform in recent years require transparency in data collection methods and sampling strategies so that research limitations can be clearly stated and more easily replicated [17].

Component	Description
Data Source	Public posts on social media X related to keywords for the Affan Kurniawan case.
Dataset file name	affan_kurniawan.csv
Initial (raw) records	10,624 entries.
Cleaning process	Removing duplicate and empty text records (drop_duplicates + dropna on the text column).
Records after cleaning	7,431 entries.
Data collection period	28 August 2025–02 September 2025 (based on the crawling time-window parameters in the notebook).
Language	Indonesian (filtered by the language column).
Main fields	tweet_id, created_time, text, like_count.
Key metadata fields	reply_count, retweet_count, quote_count, tweet_url, user_id, username, image_url, location, reply_to_user.
Preprocessing output columns (in the notebook)	cleaning, case_folding, normalisasi, tokenize, stopword removal, stemming_data.
Sentiment labels	positive / negative / neutral (automatic lexicon/rule-based labeling).
Label distribution (after labeling)	Positive: 1,395; Negative: 3,735; Neutral: 2,301 (total 7,431).
Training–testing data split	Train–test split — 80:20 → training: 5,944; testing: 1,487.

Table 1 - Dataset overview

The next stage is text preprocessing and sentiment labeling. Preprocessing is conducted to improve data quality prior to modeling and includes case folding, removing URLs, mentions, numbers, punctuation, and non-alphabetic characters, followed by tokenization, stopword removal, and Indonesian stemming using the Sastrawi library. Such preprocessing steps are recommended in social media sentiment analysis because they effectively reduce noise and improve classification performance. After preprocessing, sentiment labeling is performed using a rule-based dictionary (lexicon) approach to categorize data into positive, negative, and neutral classes. This automatic labeling approach is commonly used in supervised-learning-based sentiment analysis studies, although it may introduce label noise, which is a limitation of the study [18].

The preprocessed text is then converted into numerical form through feature representation using the Bag-of-Words (BoW) method with CountVectorizer. This method represents each document as a word-frequency vector and is widely used in classical machine-learning-based sentiment analysis due to its simplicity and compatibility with Naïve Bayes and Support Vector Machine (SVM) algorithms for handling high-dimensional text data. The BoW approach has been widely applied in social media sentiment analysis, particularly in studies comparing the performance of classical text classification algorithms such as Naïve Bayes and SVM [19]. The use of BoW feature representation via CountVectorizer in this study is also supported by recent findings showing that BoW remains competitive as a baseline across many text classification tasks, especially when research emphasizes interpretability, transparency, and method comparison [20]. The feature-representation scheme used in this study is illustrated in Figure 2.

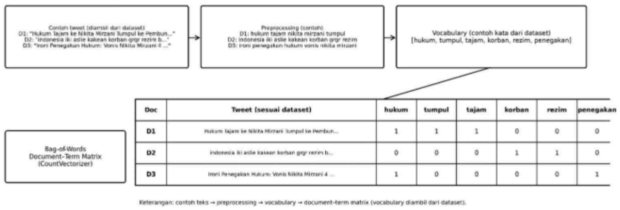

Figure 2 – Feature representation using Bag-of-Words

The dataset represented as numerical features is then split into training and testing sets using an 80:20 train–test split. The split is stratified by sentiment labels to maintain balanced class proportions between the training and testing sets. This step ensures that model evaluation is conducted on data not used during training so that performance can be measured objectively.

In the modeling stage, two classification algorithms are applied and compared: Naïve Bayes and Support Vector Machine (SVM). Naïve Bayes serves as an efficient probabilistic baseline model for discrete text data, while SVM is a margin-based model that is effective for high-dimensional data. Comparing these two algorithms is common in sentiment analysis research to evaluate differences in model performance on social media text data [21]. Comparative studies on social media data also suggest that evaluating multiple classifiers on the same dataset provides an objective view of each method's strengths and limitations, particularly when the data are imbalanced and vocabulary is diverse [22].

Model performance is evaluated on the test set using accuracy, precision, recall, and F1-score. In addition, confusion matrices are used to analyze classification errors for each sentiment class in more detail. Confusion-matrix-based evaluation provides a more comprehensive view of a model's ability to distinguish sentiment classes and complements aggregate performance metrics [23].

3. RESULTS AND ANALYSIS

Based on the data processing workflow in the notebook, the dataset was split using an 80:20 train–test split, so evaluation was performed on test data that were not used during training. Text features were represented using Bag-of-Words (BoW) with CountVectorizer, producing high-dimensional vectors suitable for classical text classification models such as Naïve Bayes and SVM. This vector-based feature representation is commonly used in Twitter/X sentiment analysis studies, particularly when the research focus is to compare the performance of traditional classification models on social media text data [10].

The class distribution in the dataset (negative, neutral, positive) indicates class imbalance, where the majority class tends to dominate evaluation if accuracy alone is used. Therefore, macro-average metrics and error-visualization through confusion matrices are required to assess performance fairly across classes. The use of confusion matrices together with precision, recall, and F1-score is recommended for multi-class classification and imbalanced datasets because it provides both aggregate performance and detailed class-wise error information [24].

Sentiment class	Count (n)	Percentage (%)
Negative	3.735	50.26
Neutral	2.301	30.96
Positive	1.395	18.77
Total	7.431	100.00

Table 2 - Sentiment class distribution

The confusion matrices summarize class-wise prediction outcomes on the 1,487 test instances (label order in the matrix follows **negatif–netral–positif**). For **Naïve Bayes**, the model correctly classified **937/1054** negative instances, while **82** negative instances were misclassified as **positif** and **35** as **netral**. The largest error occurs in the **netral** class: only **54/257** netral instances were predicted correctly, with **179** netral instances misclassified as **negatif** and **24** as **positif**. For the **positif** class, Naïve Bayes correctly predicted **117/176**, while **55** were misclassified as **negatif** and **4** as **netral**. This pattern indicates that Naïve Bayes tends to shift ambiguous or minority-class instances—especially **netral**—toward the majority class (**negatif**), which aligns with its lower netral recall and macro-average performance.

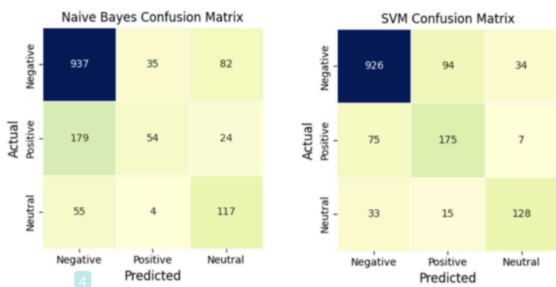

Figure 3 - Confusion matrix Naïve Bayes & SVM

The evaluation results on the test set show that SVM achieved higher performance than Naïve Bayes in both accuracy (0.826 vs 0.745) and macro F1-score (0.759 vs 0.579). This indicates that SVM is not only strong on the majority class but also more consistent on minority classes, especially neutral. The confusion matrices support this finding: Naïve Bayes correctly classified only 54/257 neutral instances, whereas SVM improved neutral performance to 175/257, reducing misclassification of neutral into the majority class (negative). Such results are consistent with comparative studies reporting that SVM often outperforms Naïve Bayes for BoW-based sentiment classification [19], while confusion matrices provide detailed class-wise error patterns beyond aggregate metrics [24].

Modeling	Class	Accuracy	Precision	Recall	F1-Score
Naïve Bayes (MultinomialNB)	negatif	0.745	0.800	0.889	0.842
	netral		0.581	0.210	0.309
	positif		0.525	0.665	0.586

	macro avg		0.635	0.588	0.579
	weighted avg		0.730	0.745	0.720
SVM (LinearSVC)	negatif	0.826	0.896	0.879	0.887
	netral		0.616	0.681	0.647
	positif		0.757	0.727	0.742
	macro avg		0.756	0.762	0.759
	weighted avg		0.831	0.826	0.828

Table 3 - Modelling Naïve Bayes and Support Vector Machine

Overall, the results of this study indicate that under the same BoW–CountVectorizer configuration and evaluation scheme, SVM (LinearSVC) outperforms Multinomial Naïve Bayes. Conceptually, SVM is effective for high-dimensional text data because it focuses on finding a decision boundary with a maximum margin, whereas Naïve Bayes relies on the feature-independence assumption, which is often not fully satisfied in natural language data. The pattern of SVM outperforming Naïve Bayes in vector-feature-based sentiment analysis tasks has also been reported in recent comparative studies [19].

The weakness of Naïve Bayes on the neutral class can be explained by (i) class imbalance that pushes the model toward the majority class and (ii) the short and ambiguous nature of X text, where neutral signals often overlap with negative/positive vocabulary in the BoW feature space. Twitter/X sentiment analysis literature emphasizes that term-frequency/BoW approaches are widely used, but classification performance can be strongly influenced by data characteristics, class distribution, and the evaluation scheme [10].

From a practical perspective, using SVM as a baseline is more advisable for monitoring sentiment toward social issues on X because it is more stable on minority classes. However, interpretation of the results should consider potential discourse bias caused by bots or inauthentic accounts that may affect language patterns and the direction of conversations; large-scale studies show that bots have linguistic characteristics that differ from humans and can change public discourse dynamics [6].

The limitations of this study include potential noise introduced by rule-/lexicon-based automatic labeling, limited coverage of public posts within a specific time period, the inability of BoW to capture sarcasm and implicit context, and the possible influence of bots/inauthentic accounts on data distribution and sentiment interpretation. Therefore, reporting appropriate multi-class metrics (macro/weighted F1-score) and confusion matrices is important for evaluation transparency and for avoiding interpretations based solely on accuracy [24].
Future research is recommended to address class imbalance (e.g., class weighting or resampling), test additional feature schemes (e.g., n-grams or TF-IDF as a comparison to BoW), tune SVM hyperparameters, use cross-validation, and integrate bot detection/filtering steps to improve the representativeness of authentic public sentiment [24].

Figure 4 - Wordcloud per sentiment class

4. CONCLUSION

This study analyzes public sentiment on social media X regarding the Affan Kurniawan case through text preprocessing, lexicon-based sentiment labeling, Bag-of-Words feature representation (CountVectorizer), and classification using Naïve Bayes and Support Vector Machine (SVM) [25]. The results and discussion indicate that public discourse is predominantly neutral (informational/factual comments), yet there remain meaningful proportions of positive sentiment (expressions of sympathy/support) and negative sentiment (anger/condemnation), reflecting both emotional responses and public evaluations of the incident and its handling [25]. Model performance was evaluated using classification metrics (accuracy, precision, recall, and F1-score) and confusion matrices to assess prediction accuracy and error patterns across sentiment classes [24]. Accordingly, RQ1 is addressed by mapping the sentiment distribution, which shows neutral dominance alongside substantial positive and negative sentiment, while RQ2 is addressed through comparative evaluation metrics, where the best-performing model is determined by a higher F1-score and more balanced misclassification patterns in the confusion matrix [24]. RQ3 emphasizes that interpreting "public sentiment" on X must consider data-access constraints and their effects on sampling and study reproducibility, making transparent reporting of data collection methods essential. In addition, the potential influence of automated accounts/bots may affect observed conversation patterns and sentiment distributions; therefore, future work is recommended to apply bot filtering or sensitivity analyses to reduce bias [6]. The contributions of this study include empirical, data-driven insights into public response tendencies toward a social issue on X, a methodological contribution through a transparent baseline comparison of Naïve Bayes and SVM using Bag-of-Words features, and a practical contribution by providing guidance for interpreting digital public-opinion dynamics with caution [25]. Future research is recommended to improve label quality through manual annotation or validated hybrid annotation to better capture sarcasm and complex context, test alternative feature representations and models, and document data-access methods and sampling decisions in detail to strengthen robustness and reproducibility [25].

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