JURNAL RISET INFORMATIKA **P-ISSN: 2656-1743 |E-ISSN: 2656-1735**
Vol. 7, No. 3. Juni 2025 DOI: https://doi.org/10.34288/jri.v7i3.361
Accredited rank 4 (SINTA 4), excerpts from the decision of the DITJEN DIKTIRISTEK No. 230/E/KPT/2023

Sentiment Analysis on Import Tariff Policy and Gold Price Increase with TF-IDF

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Abstract

Global economic policy changes, such as Donald Trump's import tariff policy in 2025, have elicited a variety of public responses recorded through social media such as Twitter. Analysis of public opinion is important for understanding public perceptions of the dynamics of gold prices as a strategic commodity. This study aims to analyze public sentiment toward tariff policy and gold issues using TF-IDF feature extraction. To address class imbalance in the tweet data, the Synthetic Minority Over-sampling Technique (SMOTE) was employed. The dataset was obtained from Twitter using the keywords "trump," "tariff," and "gold," followed by preprocessing and sentiment labeling (positive, negative, neutral). The analysis results show that 88.8% of tweets contain positive sentiment, 6.9% negative, and 4.1% neutral toward Donald Trump's tariff increase policy. These findings indicate that the tariff policy issue is viewed optimistically by the public as it is perceived to benefit gold prices. The model evaluation results before applying the SMOTE technique were 81.23%, with the highest precision in the positive class (0.81) and recall of 1.00. After applying the SMOTE technique, the dataset distribution was more balanced with a recall of 0.87 and an increase in accuracy to 84.22%.

Keywords: gold, sentiment analysis, social media, SMOTE, TF-IDF

Abstrak

Perubahan kebijakan ekonomi global, seperti kebijakan tarif impor oleh Donald Trump pada tahun 2025, menimbulkan beragam respons publik yang terekam melalui media sosial seperti Twitter. Analisis terhadap opini publik ini menjadi penting untuk memahami persepsi masyarakat terhadap dinamika harga emas sebagai komoditas strategis. Penelitian ini bertujuan untuk menganalisis sentimen masyarakat terhadap isu kebijakan tarif dan emas menggunakan ekstraksi fitur TF-IDF. Untuk mengatasi ketidakseimbangan kelas dalam data tweet, digunakan teknik Synthetic Minority Over-sampling Technique (SMOTE). Dataset diperoleh dari Twitter dengan kata kunci "trump", "tarif", dan "emas", kemudian dilakukan preprocessing serta pelabelan sentimen (positif, negatif, netral). Hasil analisis menunjukkan bahwa 88,8% tweet mengandung sentimen positif, 6,9% negatif, dan 4,1% netral terhadap kebijakan kenaikan tarif yang dilakukan oleh Donald Trump. Temuan ini menunjukkan bahwa isu kebijakan tarif diasosiasikan secara optimis oleh publik karena dianggap menguntungkan harga emas. Sedangkan untuk hasil evaluasi model sebelum dilakukan teknik SMOTE sebesar 81,23%, dengan precision tertinggi pada kelas positif (0.81) dan recall 1.00. Hasil setelah dilakukan teknik SMOTE, terlihat penyebaran dataset cukup seimbang dengan recall 0.87 dan kenaikan akurasi menjadi 84.22%.

Kata kunci: analisis sentimen, emas, media sosial, SMOTE, TF-IDF

INTRODUCTION

Gold is one of the most stable and trusted investment instruments globally, especially during times of economic and geopolitical uncertainty (Septiana & Zulkifli, 2024). The upward trend in global gold prices is likely due to several factors, one of which is fundamental and macroeconomic factors that affect the supply and demand of gold (Al Wahhab KH & Masruroh, 2025). Significant changes in gold prices can be triggered by various factors, ranging from inflation and interest rates to strategic economic policies of developed countries (Sunaryo, 2022). In 2025, Donald Trump's re-evaluation of import policies during his presidency became the focus of public and global media attention. This policy elicited mixed responses from the public, including concerns about the disruption of international trade and its impact on exchange rates and commodities such as gold (Suparmono, 2018). To that end, analyzing public perceptions and reactions is crucial to understanding how public sentiment evolves in line with policy changes (Anisa, 2023).

With the development of information technology, social media such as Twitter has become an open space that reflects public opinion and perceptions in real time (Zainu Ridlo et al., 2024). Data from social media has great potential as an alternative source in economic and social studies.

Several studies have used Twitter to understand public perceptions of social and economic issues. Research by (Tesalonika & Mailoa, 2024) and (Iskandar Mulyana & Lutfianti, 2023) applied classical algorithms such as Naïve Bayes and SVM to analyze sentiment toward the issue of economic recession in Indonesia using Twitter data. Both studies showed good accuracy performance, but did not include data balancing approaches such as SMOTE, and were still limited to domestic issues with a narrow scope. Another study by (Eka Putra et al., 2023) using a lexicon-based approach (TextBlob, VADER) to classify sentiment toward the judicial system and recession, but has not yet implemented a machine learning model or systematically evaluated classification performance. In addition, (Savira et al., 2023) in his research utilizing SVM for sentiment analysis of fuel price increases, but it was limited in terms of dataset size and did not address data imbalance.

To improve the accuracy of understanding the context of sentences in tweets, an N-Gram-based Natural Language Processing (NLP) approach was used in this study. N-Gram allows the model to understand the relationship between words in sequence, so that phrases such as “did not rise” or “gold prices fell” are not misinterpreted as positive sentiment simply because they contain the words ‘rise’ or “gold”.

Based on this review, it can be concluded that the majority of previous studies still have limitations in several aspects: (1) data sources that do not reflect public opinion broadly, (2) lack of handling of unbalanced data (class imbalance), (3) few studies linking sentiment analysis to specific issues such as foreign policy or global commodities like gold, and (4) insufficient integration of n-gram-based NLP approaches with modern classification and oversampling techniques such as SMOTE.

This study integrates data from Twitter that is directly related to the issue of gold and Donald Trump's trade policy in 2025, which has not been examined in previous literature. The approach used combines TF-IDF NLP techniques, along with the application of SMOTE to address data imbalance issues, and performs classification using the Naive Bayes algorithm. In addition to focusing on sentiment classification, this study also links public sentiment results with gold price dynamics, thereby contributing to real-time public opinion-based economic analysis.

RESEARCH METHODS

The research was conducted with the aim of analyzing public sentiment towards the increase in gold prices as a result of the US President's policy to raise import tariffs on China. (Hendarto, 2025). Data obtained from social media X, by linking keywords “kenaikan tarif impor Trump” with “kenaikan harga emas”.

The data period is from February 2, 2025, to April 30, 2025, with a total of 3,015 data points and 3,033 comment lines. The stages of the research conducted are presented in Figure 1.

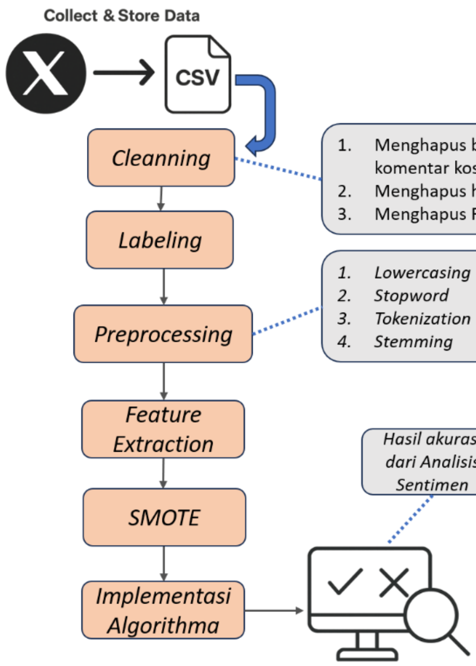

Figure 1. Research stages

Cleaning is performed to remove empty comment lines, delete http addresses, remove and remove retweets (RT) as they will interfere with the next process. Data

Cleaning techniques, combined with regular expressions (regex), can identify and eliminate these unnecessary characters, thereby improving the overall quality of the dataset(Mirdan et al., 2025). After cleaning the obtained text data, automatic labeling is performed using a lexicon. Then, the preprocessing stage.

Preprocessing is an important step in normalizing text data by*:*

a. *Lowercasing*

Table 1 *Lowercasing*

Harga Emas Antam Naik Rp6000 Didorong Kenaikan Emas Dunia dan Kekhawatiran Ekonomi AS	harga emas antam naik rp6000 didorong kenaikan emas dunia dan kekhawatiran ekonomi as
Jika dihitung dengan misal inflasi 4tahun harusnya udah lebih dari Rp6000 tarifnya Sementara kalo dari kenaikan ump di 2005 Rp711843 ke 2025 Rp5396760 udah lebih dari 7x Kalo secara ke ekonomian dan tanpa emosi harunya tarif di tahun 2025 udah sekitar Rp10000	jika dihitung dengan misal inflasi 4tahun harusnya udah lebih dari rp6000 tarifnya sementara kalo dari kenaikan ump di 2005 rp711843 ke 2025 rp5396760 udah lebih dari 7x kalo secara ke ekonomian dan tanpa emosi harunya tarif di tahun 2025 udah sekitar rp10000

b. *Stopword*
This step removes words that are considered unimportant. Sometimes, some very common words that seem useless in helping to select documents that match the user's needs are excluded from the vocabulary entirely (Findawati & Rosid, 2020).

c. *Tokenization*
Sentence tokenization is performed to obtain all words in a sentence, in the form of a list of words (Findawati & Rosid, 2020).

d. *Stemming*
Stemming is the process of converting words to their base form (stem) in order to standardize the morphological variations of a word for easy analysis, such as the word "berlari", "lari", "pelari" and "berlarian" from the word "lari".

Feature extraction is an important stage in the data processing process, including sentiment analysis, which aims to convert raw data (such as text) into numerical or symbolic representations that can be understood and processed by machine learning algorithms. Where the learning algorithm does not support string-type data (Darmawan et al., 2023). TF-IDF is a pre-training algorithm that transforms review texts into numerical data (Vijayaraghavan & Basu, 2020). This study uses Term Frequency-Inverse Document Frequency (TF-IDF).

This method combines two ideas: measuring how frequently a term appears in a document and how unique the term is by counting how many documents in the collection contain the term (Setiawan et al., 2024). TF-IDF is used to calculate the weight of each word most commonly used in information retrieval. This method is also efficient, easy, and accurate (Findawati, 2020). Here are the equations created in numbers (1), (2), and (3).

$$Wa,t = tf\ dt * IDF \qquad (1)$$

$$\text{tfd} = \frac{(Frequency\ of\ term\ t\ in\ a\ document)}{Total\ number\ of\ terms\ in\ the\ document} \qquad (2)$$

$$IDF = \log_2 \frac{d}{df} \qquad (3)$$

Where:
W = weight of document n
d = document
t = keyword
tf = term frequency (number of occurrences of a word)
IDF = inverse document frequency

Then, the SMOTE technique was used to balance the existing dataset, and the Naive Bayes algorithm was implemented to generate the F1-score accuracy value.

RESULTS AND DISCUSSION

The following are the results of data processing. A word cloud is a text data visualization technique that is effective for analysis, surveys, and the collection of written opinions, as well as other applications(Hossain et al., 2021). There are words that frequently appear in X's tweets with the keyword “kenaikan tarif impor Trump” and “kenaikan harga emas”. The word that appears most frequently is the word “naik”, “harga”, “yg”, “jadi”, “gaji”. The occurrence of a word is the number of times that word appears in the dataset, as shown in Figure 2.

Figure 2 *WordCloud*

The dataset is divided into several classes: positive, negative, and neutral. In real-world datasets, it is common to encounter situations where the number of instances in one class is significantly lower than in other classes. This condition is referred to as the class imbalance problem (Sutoyo & Fadlurrahman, 2020). The distribution of the dataset is shown in Figure 3, with 4,924 positive labels, 584 negative labels, and 510 neutral labels. The distribution is heavily skewed toward positive labels..

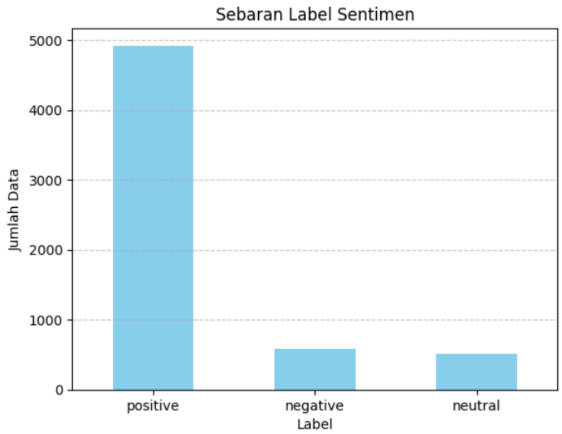

Figure 3 Class distribution

The preprocessing stage produces lowercasing, which is presented in Table 1, namely lowercasing. Table 2 presents the data after preprocessing.

Table 2 Preprocessing Results

Preprocessing Results
tarik nyicil btc harga sekarang naik aset gak signifikanmakanya lebih pilih nyicil sol sui beberapa altcoin lain maks koin
fessponti kan memang naik tdlnya kalau naik kali lipat perlu tanya sih nder sa cuma naik k rerata bayar bulan
kapolres simalungun pimpin upacara naik pangkat luar biasa personel polres simalungun
catat harga berangkat ubah ikut kurs dollar birokrasi arab saudi harga masuk paspor vaksin miningitis pribadi jamaah masuk transport kota asal jakarta masuk lounge naik harga room hotel tiket
vgl wkwkwk aja aku naik kelas tdk sering pernah beri paksa guru tdk minta beri sbg ucap terimakasih gak gratifikasi guru iku
cnnindonesia bukan soal gratifikasi bukan sih bagaimana jaga marwah guru sbg didik jadi stop kasih barang guru pas naik kelas momen apa video diunggh medsos
tanyakanrl waktu smp aku ekskul pramuka d kasih soal uji naik tingkat d tanya siapa bapak pramuka dunia aku sadar penuh nulis nama guru bimbing pramuka ku dong
bukankah angka nikah lahir menurunnegara usaha menujang memfasilitasitapi indonesiaseharusnya turun angka korupsikalau naik pajak dalih rakyatcoba lihat lapang dg seksama dprri mprgoid kpkri kemendagri setkabgoid kemensetnegri
harga daging ayam hingga cabai rawit merah alami naik

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The next step is feature extraction, which involves converting data into numerical values so that it can be easily read by machine learning. Feature extraction is one of the most important techniques in data mining and in calculating feature values within a document(Zahri et al., 2023). Figure 4 shows several documents. In the first document, each word is counted. For example, in row index 0, the word abdi does not appear in the first document, so the value obtained is 0. The feature extraction results are presented in Figure 3.

	abdi	abis	acara	ada	adadikompas	adil	ai	air	aja	ajar	...	\
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.152747	0.0	...	
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...	

Figure 4 TF-IDF process results

Before implementation into the algorithm, the distribution of labels in the dataset must not be dominant in one label, such as the dataset presented, which is dominant in positive labels. To overcome this problem, the SMOTE technique is used, so that the results can be seen in Figure 5. Figure 5 shows the distribution of the dataset before SMOTE, where positive labels are more dominant, and the distribution of the dataset after SMOTE, where the distribution of the dataset is balanced.

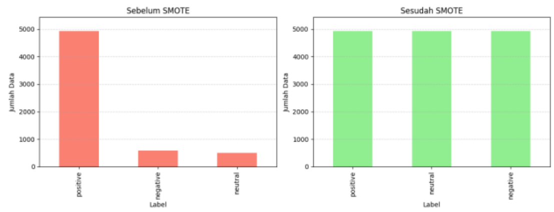

Figure 5. Distribution before and after SMOTE

Implement the results of the TF-IDF calculation into the Naive Bayes algorithm, resulting in an accuracy value of 81.23%., as presented in Table 3.

Table 3 Accuracy results before SMOTE

	Precision	Recall	F1-score	Support
Negative	0.71	0.04	0.08	126
Neutral	0.67	0.07	0.13	109
Positive	0.81	1.00	0.90	969
Accuracy			0.81	1204
Macro avg	0.73	0.37	0.37	1204
Meighted avg	0.79	0.81	0.74	1204
Accuracy : 81.23%				

Based on Table 3, an analysis can be carried out related to each class, namely:
Positive class:
1. Precision 0.81 positive prediction is correct
2. Recall 1.00 all positive data are successfully recognized
3. F1-score 0.90, the model is very good at detecting positive classes

Negative class:
1. Precision 0.71, meaning 71% of negative predictions are correct
2. Recall 0.04, only 4% is very low
3. F1-score 0.08, the model fails to recognize the negative class

Neutral class:
1. Precision 0.67
2. Recall 0.07 means very low
3. F1-score, 0.13, the model almost does not recognize neutral tweets.

The conclusion from Table 3, that with an unbalanced dataset distribution the results will lean towards the positive label as seen in Recall, which is 1.00.

Table 4 Accuracy results after SMOTE

	Precision	Recall	F1-score	Support
Negative	0.49	0.70	0.58	126
Neutral	0.55	0.75	0.63	109
Positive	0.96	0.87	0.92	969
Accuracy			0.84	1204
Macro avg	0.67	0.77	0.71	1204
Meighted avg	0.88	0.84	0.85	1204
Accuracy : 84.22%				

Table 4 presents different results from Table 3, it can be seen that Recall in a balanced position does not dominate one of the labels. Accuracy has increased to 84.22%. The final stage is to analyze the relationship between “kenaikan tarif impor Trump” with “kenaikan harga emas”, with keywords “tarif”, “trump” and “emas” the results obtained are as presented in Table 5.

Table 5 Keyword Distribution

Label	*Total*
Positive	0.888446
Negative	0.069721
Neutral	0.041833

CONCLUSIONS AND SUGGESTIONS

Based on the analysis of tweets containing the keywords “trump”, “tariff”, and “gold”, it was found that 88.8% contained positive sentiment. This indicates that the public generally responded to the issue with optimism, which may have been triggered by the perception that the increase in tariffs was driving up the price of gold — an asset considered safe amid uncertainty. In contrast, only 6.9% of tweets showed negative sentiment, and 4.1% were neutral. After SMOTE was performed on the data, the accuracy value was 84.22%, meaning that it is important to SMOTE the dataset so that the results are in accordance with the balance of the existing dataset.

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P-ISSN: 2656-1743 |E-ISSN: 2656-1735
DOI: https://doi.org/10.34288/jri.v6i1.XXX
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