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## Sentiment Analysis of Indonesian Nickel Downstreaming on X Using Naïve Bayes and K-Nearest Neighbors

Zulfitriah Kurniawan Mustafa, Anastasia Lidya Maukar\*, Galih Prakoso and Rowan Abdelhaleem

**Abstract** – Nickel downstreaming is one of Indonesia's most prominent industrial policies, intended to drive economic growth and strengthen its role in the global electric vehicle supply chain. This study applies sentiment analysis to 337 tweets from X (formerly Twitter) to examine public perceptions of the policy. Using Naïve Bayes and K-Nearest Neighbors algorithms, sentiments were classified as positive, negative, or neutral and evaluated through accuracy, precision, recall, and F1-score. Results indicate that negative sentiment dominates, with Naïve Bayes performing better in accuracy and recall, while KNN showed strengths in precision and F1-score. Wordcloud analysis reveals positive narratives around industrial progress and national pride, negative views centered on environmental risks and foreign control, and neutral sentiments reflecting factual reporting. These findings highlight nickel downstreaming as a contested policy, balancing economic ambitions with social and ecological concerns. The study demonstrates the value of sentiment analysis for policy research, offering real-time insights into public opinion to support more inclusive and sustainable governance

**Keywords:** Nickel Downstreaming, Sentiment Analysis, Naïve Bayes, K-Nearest Neighbors, Social Media, Public Perception, Indonesia.

### I. INTRODUCTION

Indonesia possesses one of the largest nickel reserves in the world, positioning the country as a critical player in the global electric vehicle (EV) industry. Nickel is a central material in lithium-ion

batteries, which dominate the energy storage technology for Evs [1]. Recognizing this strategic advantage, the Indonesian government introduced downstreaming policies that prohibit the export of raw ore and prioritize domestic processing. This transformation is presented not only as an economic strategy but also as a statement of industrial sovereignty, with investment in smelters and battery plants growing rapidly, generating employment and strengthening the national trade balance [2].

The importance of nickel in the broader energy transition has been widely acknowledged. Putri & Saufica argue that nickel is inseparable from the green economy, particularly in accelerating renewable energy systems.[3] Similarly, Farawansa highlights that downstreaming reflects a developmental state model that aligns industrial growth with governance and environmental considerations. These perspectives show how nickel is framed both as a strategic commodity and as an instrument for asserting Indonesia's position in global value chains [4].

Despite its potential, the downstreaming agenda has drawn criticism from multiple directions. Civil society groups point to the ecological costs of mining and smelting, including deforestation, waste mismanagement, and water pollution. Social challenges also emerge in the form of land disputes and the perception of unfair profit distribution, where investors, rather than local communities, capture benefits [5].

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Marwanto et al. emphasize that public debate often questions whether downstreaming truly strengthens sovereignty or simply deepens foreign control over natural resources [6]. This duality creates polarized narratives: for some, nickel is a symbol of progress, while for others it represents ecological risk and inequality.

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In today's digital landscape, debates on such issues no longer occur solely through formal channels. Platforms like X (formerly Twitter) provide real-time spaces for public expression and contestation [7]. Leelawat et al. note that social media has become an effective medium to monitor opinion dynamics around national policies [8]. Vindua & Zailani further observe that politically literate urban communities dominate these discussions, turning X into a vibrant forum where narratives about industrial policy, energy transition, and justice are continuously reshaped [9]. The platform therefore, functions not only as a communication tool but also as a repository of public sentiment, reflecting both enthusiasm and resistance toward downstreaming.

To analyze these dynamics, sentiment analysis offers an important methodological approach. Devika et al. describe sentiment analysis as the extraction of subjective information from unstructured texts, allowing researchers to determine whether expressions are positive, negative, or neutral [10]. Parveen & Pandey add that the technique has been applied widely in fields ranging from politics to business, demonstrating its ability to capture attitudes at scale [11]. Unlike surveys, which are bound by time and limited respondents, sentiment analysis leverages vast amounts of spontaneous online data, offering more immediate insights into collective opinion.

The foundation of sentiment analysis lies in classification. As Soofi & Awan explain, text classification is a supervised learning process where input features are mapped into discrete labels such as sentiment categories [12]. Because tweets often contain slang, emojis, and inconsistent spelling, preprocessing is essential to clean the data and improve accuracy. Krouska et al. argue that preprocessing steps like tokenisation and normalisation directly enhance NLP performance, while Nurhadi et al. show how case folding reduces redundant vocabulary that can otherwise distort

classification [13]. These techniques ensure that sentiment models work with standardized input, making the results more reliable.

This study applies two popular classification algorithms: Naïve Bayes and K-Nearest Neighbors (KNN). Naïve Bayes is a probabilistic classifier based on Bayes' Theorem and is known for being computationally efficient with high-dimensional data such as tweets. Dey et al. demonstrate its consistent strength in handling short texts despite its assumption of feature independence [14]. KNN, in contrast, classifies data by calculating distances between feature vectors, making it intuitive and straightforward. Zhang. report that KNN performs effectively when paired with TF-IDF weighting, especially in medium-scale datasets [15].

Empirical research reveals differences in the performance of the two algorithms. Wongkar et al. found that Naïve Bayes achieved higher precision in tweet classification, outperforming KNN [16]. Ndamhuri et al. later confirmed that while KNN can reach competitive accuracy, Naïve Bayes remains more stable in contexts where language is informal, and data is noisy, as is often the case on social media [17]. These findings justify the comparative use of both models in this study.

The Indonesian case of nickel downstreaming provides a timely context for such an analysis. The policy is economically significant, socially divisive, and globally relevant [18]. It is celebrated as a driver of industrial modernization, but contested for its environmental and equity implications. By analyzing tweets collected through hashtags such as #NikelIndonesia and #SaveRajaAmpat, this study applies Naïve Bayes and KNN to classify public opinion into positive, negative, and neutral categories. Through this dual approach, the research not only evaluates algorithmic performance but also illuminates how Indonesians perceive one of their most ambitious national strategies.

## II. MATERIALS AND METHODS

This study used data collected from X (formerly Twitter) using the official API in Python, focusing on hashtags and keywords closely related to nickel downstreaming, including “kebijakan hilirisasi”, #HilirisasiNikel, #NikelIndonesia, and #SaveRajaAmpat. In the early stages of scraping, broader keywords such as “nikel” and “hilirisasi nikel” were also tested. However, these terms produced a large number of irrelevant tweets, reducing topic consistency. Therefore, the final selection of keywords was refined to ensure that the retrieved tweets specifically addressed the nickel downstreaming policy. The inclusion of the hashtag #SaveRajaAmpat was deliberate, as it gained prominence between January 2024 and May 2025 amid public discourse on environmental impacts linked to nickel mining activities in Raja Ampat. Despite its environmental focus, the hashtag was maintained to reflect a wider spectrum of public sentiment surrounding the downstreaming issue. A total of 337 tweets were collected, which, although relatively limited, is

considered adequate for exploratory sentiment analysis in policy-related research—where tweet relevance and contextual depth are prioritized over data volume. Duplicate posts, retweets, and spam-like content were filtered out during preprocessing to ensure that only original, contextually relevant tweets were retained. Manual verification was also performed to remove off-topic content, though a small margin of unrelated entries may remain due to the informal nature of social media discourse. The collected data, restricted to tweets written in Indonesian (lang:id) and posted between January 2024 and May 2025, thus provides a focused and representative snapshot of public opinion on Indonesia's nickel downstreaming policy. The tweet was then refined through several preprocessing steps, including case folding, stopword removal, and stemming. These steps were necessary because tweets are often noisy, containing slang, abbreviations, and inconsistent spelling. Krouska et al., note that proper preprocessing significantly improves the performance of sentiment classification [19]. After preprocessing, the dataset was ready for feature extraction using Term Frequency–Inverse Document Frequency (TF–IDF). The dataset was then randomly divided into 80% training and 20% testing data using a fixed random seed to ensure reproducibility and maintain proportional class distribution. The research steps can be depicted as a flowchart in Figure 1.

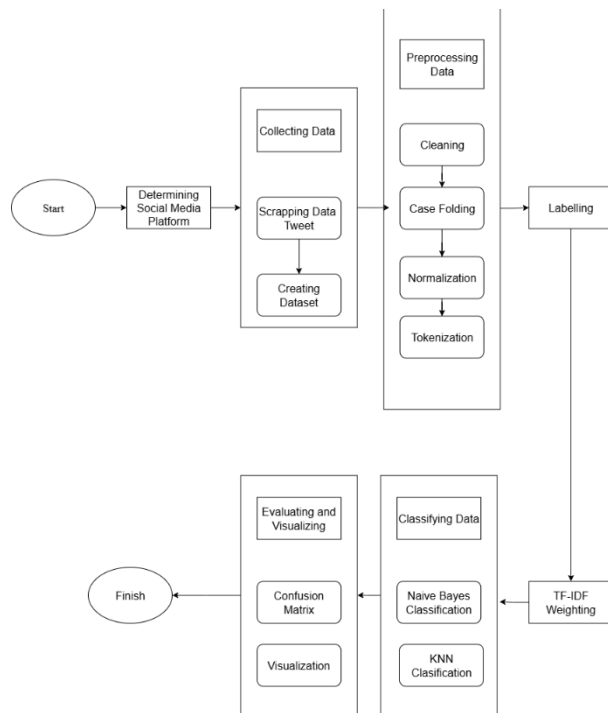


FIGURE 1. Research steps flowchart

Tweets were labeled into positive, negative, and neutral categories before classification. Sentiment labeling was performed automatically using an Indonesian lexicon-based scoring approach. Each token was assigned sentiment polarity (+1, 0, -1). Tweets containing negations or emojis were normalized during preprocessing to reduce polarity bias. By applying this method, the dataset reflected actual tendencies in public opinion about nickel downstreaming [20]. The inclusion of neutral

sentiment also made the classification task more challenging, as neutral texts often overlap linguistically with positive or negative expressions. The calculation of sentiment labelling can be expressed in (1) [21]:

$$\text{Score} = \sum \text{Positive Words} - \sum \text{Negative Words} \quad (1)$$

Feature extraction was carried out using Term Frequency–Inverse Document Frequency (TF–IDF). Term Frequency measures how often a term occurs in a document, as formulated in (2). Inverse Document Frequency reduces the weight of common terms across the corpus, as shown in (3). Multiplying TF and IDF yields the final TF–IDF weight, presented in (4). According to Xiang, TF–IDF is effective in highlighting discriminative words while minimising noise from frequent but less informative terms [22].

$$TF-IDF(d, t) = TF(d, t) * IDF(t) \quad (2)$$

$$TF(d, t) = \frac{\text{number of } t \text{ words in document } d}{\text{total words in document } d} \quad (3)$$

$$IDF(t) = \frac{\text{total documents}}{\text{no of documents have word } t} \quad (4)$$

Naïve Bayes is a probabilistic model that applies Bayes' Theorem to text classification. The general theorem is written in (5). Joint probability for features is expressed in (6), while the independence assumption simplifies the model (7). Studies such as Fauzi et al. demonstrate that Naïve Bayes remains highly effective for short and sparse texts like tweets due to its computational efficiency [18].

$$P(C|X) = \frac{p(X|C)p(c)}{p(x)} \quad (5)$$

Where:

$X$  : features or attributes in the data

$C$  : the predicted class

$P(C|X)$ : probability that  $C$  happens when  $X$  is observed

$P(X|C)$  : probability of seeing  $X$  if  $C$  its true

$P(C)$  : probability of event  $C$

$P(X)$  : probability of event  $X$

$X$  can be written as (6)

$$X = (x_1, x_2, \dots, x_n) \quad (6)$$

$$P(C | x_1, x_2, x_n) = P(C) \prod_{i=1}^n P(x_i | C) \quad (7)$$

K-Nearest Neighbors (KNN) classifies a new instance by considering the majority class among its  $k$  nearest neighbors. In this study, the distance between vectors was calculated using the Euclidean Distance, as written in (8). This approach measures similarity in a multidimensional space rather than relying on probability. KNN is a reliable option for sentiment analysis when combined with TF–IDF features [28]. In this research, KNN was used to compare the performance of distance-based classification with probabilistic classification.

The general procedure of KNN can be summarised as follows:

1. Feature Representation – In this step, the raw text data is converted into a numerical format so that it can be processed computationally. This study uses Term Frequency–Inverse Document Frequency (TF–IDF) to represent each text as a weighted vector, where the weight reflects the importance of a term relative to its frequency in the entire dataset.
2. Select Parameter k – Determine The parameter k determines the number of nearest neighbours to be considered when assigning a class label. This choice is crucial for model performance: smaller k values increase sensitivity to noise and outliers, while larger k values create smoother decision boundaries but risk missing local patterns. Common methods for selecting k include cross-validation to test performance on multiple values, heuristic rules such as using the square root of the number of training samples, and empirical trial-and-error. The optimal k depends on the dataset's characteristics and the specific classification goals.
3. Distance Calculation – Once the features are represented numerically, the distance between the query instance and each training instance is computed. This study uses the Euclidean distance, as shown in (8), which measures similarity based on the geometric distance in the feature space[23].

$$d(p, q) = \sqrt{\sum_{i=1}^n (p_i - q_i)^2} \quad (8)$$

4. Neighbor Selection – After calculating the distances, the algorithm identifies the k closest data points (neighbors) to the query instance. These neighbors serve as the basis for determining the predicted class [24].
5. Majority Voting – Finally, the query instance is assigned to the class most frequently occurring among its k nearest neighbors. This step finalizes the classification decision [25].

Model performance was measured with Accuracy, Precision, Recall, and F1-score. Accuracy is calculated as shown in (9). Precision is given in (10), while Recall is expressed in (11). Finally, the F1-score that balances Precision and Recall is defined in (12). Combining multiple evaluation metrics provides a more reliable comparison of classifiers [26].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (9)$$

$$Precision = \frac{TP}{TP + FP} \quad (10)$$

$$Recall = \frac{TP}{TP + FN} \quad (11)$$

$$F1 - Score = \frac{2 * Precision * Reccal}{Precision + Reccal} \quad (12)$$

### III. RESULT AND DISCUSSION

The analysis of public sentiment regarding Indonesia's nickel downstreaming policy began with the collection of data from X. Tweets were gathered using the hashtags #NikelIndonesia and #SaveRajaAmpat, which were chosen because they directly reflect the discourse around national industrial strategies and environmental concerns. It contains

diverse perspectives, ranging from supportive comments about industrial progress to criticisms of ecological damage and foreign involvement. The balanced nature of this dataset allows for a meaningful evaluation of machine learning algorithms while also reflecting the polarised debate around downstreaming.

The sentiment distribution generated by the Naïve Bayes classifier, as shown in Figure 2, indicates that 59.9% of the tweets were categorized as negative and 40.1% as positive. This demonstrates that unfavorable perceptions toward nickel downstreaming dominate public discussions, with criticisms outweighing expressions of optimism.

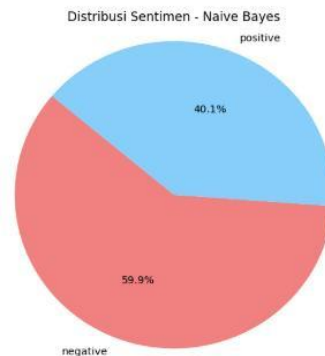


FIGURE 2. Pie chart of naïve bayes

The negative majority suggests that issues such as environmental damage, resource exploitation, and foreign involvement are salient concerns among users on X. In contrast, positive tweets reflect enthusiasm for industrial progress and the opportunities created by the electric vehicle supply chain. These results support the view that social media often amplifies critical voices, especially when policies are perceived as disruptive to ecological or social stability [27].

The K-Nearest Neighbors classifier produced a sentiment distribution, as displayed in Figure 3, in which 55.5% of the tweets were categorized as negative, 35.3% as positive, and 9.2% as neutral.

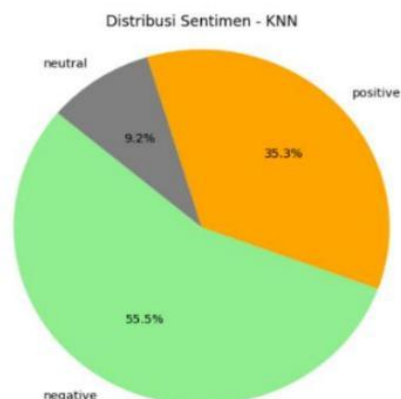


FIGURE 3. Pie chart of KNN

Compared to Naïve Bayes, KNN showed a higher proportion of negative classifications and a lower proportion of positive ones, indicating that the algorithm tends to reinforce majority categories in the dataset. The relatively small percentage of neutral sentiment suggests that KNN struggled to maintain

separation between factual or non-judgmental content and evaluative opinions. This pattern reflects the algorithm's reliance on distance measures in feature space, where overlapping vocabularies make it difficult to distinguish subtle differences. Previous studies have noted similar limitations, emphasising that KNN can underperform in short-text contexts with high dimensionality [28].

Figure 4 presents the confusion matrix of Naïve Bayes classifier. It further illustrates the classification performance of Naïve Bayes. Out of 128 tweets labeled as positive, 113 were correctly classified, while 15 were misclassified as negative. The neutral category revealed weaknesses, with 17 tweets incorrectly predicted as positive and 27 as negative, leaving none accurately detected as neutral. Meanwhile, the negative class showed the strongest results, with 160 tweets correctly predicted and only 5 misclassified as positive. This imbalance indicates that while the algorithm is highly reliable in detecting negative sentiment, it struggles with neutral tones, reflecting the difficulty of handling ambiguous or mixed expressions in short-text data [16].

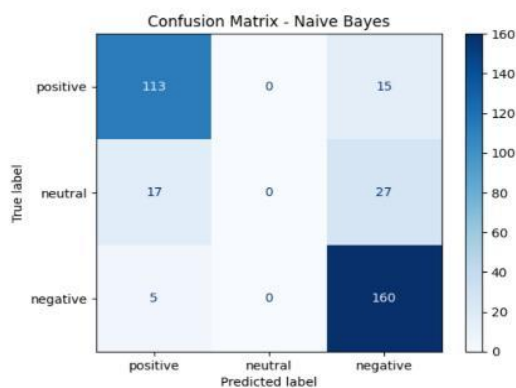


FIGURE 4. Confusion matrix of naïve bayes

The confusion matrix for the K-Nearest Neighbours classifier, as shown in Figure 5, demonstrates more significant weaknesses compared to Naïve Bayes. Out of all positive tweets, 92 were correctly identified, while 28 were misclassified as negative and eight as neutral. The neutral class again presented the greatest challenge, with only eight tweets correctly classified, whereas 16 were misclassified as positive and 20 as negative.

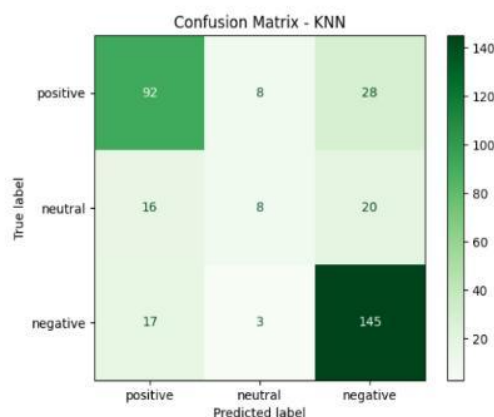


FIGURE 5. Confusion matrix of KNN

For the negative class, 145 tweets were correctly identified, but 17 were misclassified as positive and three as neutral, showing that even the strongest category was less precise than under Naïve Bayes. These results underscore the vulnerability of KNN when working with overlapping linguistic features, where slight variations in vocabulary can shift predictions into incorrect categories. The consistent underperformance in identifying neutral sentiment further suggests that KNN is less reliable in capturing subtle or factual tones. Both models showed difficulty in identifying neutral sentiment due to the linguistic ambiguity common in social media, where neutral statements often share vocabulary with positive or negative contexts. This limitation has been observed in prior studies analysing short-text sentiment [11].

The comparative evaluation of performance metrics highlights important differences between Naïve Bayes and K-Nearest Neighbors. As seen in Figure 6, Naïve Bayes achieved higher accuracy at 0.81, while KNN scored lower at 0.73, suggesting that overall predictions made by Naïve Bayes were more reliable. Interestingly, precision was stronger in KNN (0.64) compared to Naïve Bayes (0.54), meaning that KNN was slightly better at reducing false positives in this dataset.

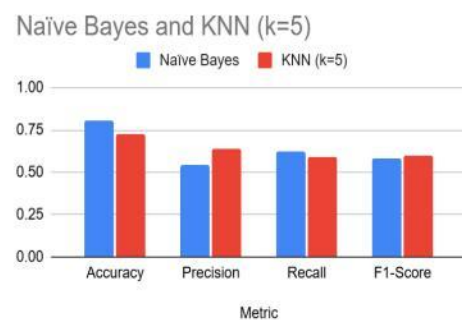


FIGURE 6. Summary of the performance based on accuracy, precision, recall, F1-score

However, recall favoured Naïve Bayes with a value of 0.62, compared to KNN's 0.59, indicating that Naïve Bayes was more effective in retrieving relevant cases. For the F1-score, which balances precision and recall, KNN obtained 0.6, marginally higher than Naïve Bayes at 0.56, showing that KNN maintained a more balanced trade-off despite its lower accuracy. These findings confirm that both algorithms have strengths and weaknesses, with Naïve Bayes excelling in accuracy and recall, while KNN demonstrates superiority in precision and F1-score [12].

As seen in Figure 7, the word cloud of positive sentiment emphasizes key terms such as *hilirisasi*, *nikel*, *Indonesia*, and *kebijakan pemerintah*, all of which highlight the framing of downstreaming as a national achievement. Words like *“investasi”*, *“ekonomi”*, and *“energi”* reinforce the perception that nickel processing is associated with industrial modernization and economic opportunity.



FIGURE 7. Word cloud of positive sentiment

The frequent presence of “kendaraan listrik” further shows the public’s optimism about Indonesia’s role in the global electric vehicle supply chain. These lexical patterns indicate that positive discourse is often tied to the promise of long-term growth, technological advancement, and global competitiveness. The emphasis on national identity through words such as “Indonesia” and “presiden” demonstrates that pride and sovereignty are central elements of supportive narratives. This pattern aligns with Farawansa’s view that developmental policies gain symbolic legitimacy when associated with progress and state strength [4].

The negative sentiment word cloud is displayed in Figure 8. It is dominated by terms such as “hilirisasi”, “nikel”, and “kebijakan”, but the surrounding vocabulary adds a critical dimension to the discourse. Words like “tidak”, “karena”, and “mahal” illustrate skepticism toward the policy’s effectiveness and its potential to increase costs for society. References to China and “tambang” highlight widespread concerns that foreign influence and extractive industries continue to benefit disproportionately from nickel exploitation.



FIGURE 8. Word cloud of negative sentiment

At the same time, the presence of words such as “dampak”, “lingkungan”, and “rakyat” shows that criticism is not only economic but also environmental and social. These lexical clusters suggest that public resistance is deeply rooted in perceptions of injustice, resource mismanagement, and ecological harm. The results confirm arguments made by Lahadalia et al., who emphasise that policies framed as nationalistic may still face rejection if they fail to address sustainability and fairness [29].

The neutral sentiment word cloud, as shown in Figure 9, highlights the dominance of terms such as hilirisasi, nikel, Indonesia, and kebijakan, which show that even non-evaluative discussions remain closely tied to the policy agenda. Words like tahun, bisa, and

masih indicate that these tweets often provide temporal or factual context, such as timelines of projects or descriptions of ongoing debates.



FIGURE 9. Word cloud of neutral sentiment

The frequent use of pemerintah, industri, and baterai demonstrates that neutral discourse still revolves around institutional actors and economic objectives, but without explicit judgment. This category reflects the role of media-like accounts or information-sharing users, who primarily reproduce reports rather than voice strong opinions. The lexical balance in this word cloud shows that neutral sentiment serves as an informational bridge, situating the debate without amplifying either criticism or support. The role of factual communication aligns with Soofi and Awan’s claim that neutral sentiment helps stabilise discourse in polarised debates by presenting descriptive content [30].

#### IV. CONCLUSION

Public responses to nickel downstreaming are shaped more by critical concerns than by optimism about economic progress. The dominance of negative sentiment indicates that ecological risks, social inequality, and questions of sovereignty remain unresolved. Optimistic expressions of pride and industrial growth exist, yet they are outweighed by scepticism. This imbalance shows that downstreaming is still perceived as a contested project rather than a shared national achievement. The overall picture is one of cautious reception rather than broad acceptance.

The application of different algorithms reveals the benefits of methodological plurality in sentiment analysis. Each model highlights distinct aspects of public expression, with one emphasizing reliability and another offering balance between metrics. These variations demonstrate that digital conversations cannot be fully captured by a single method. Cross-model evaluation strengthens confidence in findings and reduces the influence of biases inherent in individual algorithms. Robust interpretations emerge when multiple analytical approaches are applied in parallel.

Narratives within the discourse follow recognizable patterns that reflect wider social dynamics. Supportive views stress industrial independence, technological progress, and national pride, while critical voices focus on environmental damage, foreign control, and social exclusion. Neutral communication provides factual grounding, circulating information without overt judgment. Together, these strands form a discourse

that is polarized but also interconnected, with each reinforcing public perceptions in different ways. The structure of language becomes a window into underlying priorities and fears.

At the level of governance, the findings indicate that downstreaming cannot rely solely on economic arguments to secure legitimacy. Industrial expansion and investment figures do not erase doubts if environmental safeguards and fair benefit-sharing remain absent. Public trust is built when development strategies are transparent, responsive, and attentive to community impacts. Without these elements, skepticism will continue to dominate despite official claims of progress. Policies that integrate growth with sustainability stand a greater chance of being embraced.

Sentiment analysis proves to be a valuable instrument for detecting these dynamics in real time. By monitoring digital conversations, policymakers and researchers gain insight into the alignment between state narratives and public expectations. Social media discussions reveal early signals of resistance as well as opportunities for building support. These insights are essential for shaping strategies that are both credible and inclusive. In the context of nickel downstreaming, sentiment analysis shows that legitimacy must be earned not through rhetoric but through action that addresses the concerns voiced by society.

#### APPENDIX

| tweet_text                                                                                                                                                                                                                                                                                                                                                       |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Refleksi dari korban kriminalisasi akibat hilirisasi nikel<br><a href="https://t.co/JTqhoL4VLk">https://t.co/JTqhoL4VLk</a>                                                                                                                                                                                                                                      |
| Walhi Beberkan Kerusakan Lingkungan Akibat Hilirisasi Nikel di Maluku Utara: Air Sungai Terkontaminasi hingga..<br><a href="https://t.co/iBU4U4OYzd">#TempoBisnis</a>                                                                                                                                                                                            |
| Ekspansi gila-gilaan konsesi tambang nikel Indonesia demi memasok sumber baterai kendaraan listrik telah menghancurkan penghidupan masyarakat adat. Laporan kedua dari seri reportase #HilirisasiOligarki dari Sulawesi Tenggara. <a href="https://t.co/c7oYIsDhvk">https://t.co/c7oYIsDhvk</a><br><a href="https://t.co/tNTO6bUm82">https://t.co/tNTO6bUm82</a> |
| Ternyata hilirisasi nikel yg diomongkan Samsul dan di cetuskan Jokowi tidak membawa kebaikan ekonomi dan ekosistem Indonesia. Bener kata ekonom Indef Faizal Basri hilirisasi guoblok Dan beginilah hilirisasi kata Bosman Mardigu. MAU DIBOHONGI SAMSUL DAN KERABATNYA? <a href="https://t.co/JAPsqDmnFk">https://t.co/JAPsqDmnFk</a>                           |
| Di balik para elit yang koar-koar pertumbuhan ekonomi ada cerita warga di lingkaran tambang yang dihantam banjir berulang karena korporasi yang menghancurkan ruang hidup dan hutan Rezim getol bicara hilirisasi nikel yang terjadi justru hilirisasi bencana ekologis                                                                                          |
| Saat menyerahkan Tambang Nikel ke China dijanji akan bangun pabrik baterai mobil dan mobil listrik sbg hilirisasi Nikel - setelah China menguasai 90 % Nikel kita ternyata hilirisasinya hanya utk buat sendok dan garpu. Modusnya persis spt KA Cepat. Ada apa dibalik ini semua ?                                                                              |
| pak bahlil lahadalia aja optimis loh indonesia jadi lokomotif asean. pasti bisa soalnya indonesia produsen nikel batu bara dan timah. so kita harus support juga donk Hilirisasi Industri karena manfaatnya banyak meningkatkan ekonomi tapi juga membuka lapangan kerja baru loh <a href="https://t.co/PTWO47By1v">https://t.co/PTWO47By1v</a>                  |
| Luhut Bohong di Maluku Utara Hilirisasi Nikel Berakibat Masyarakat Miskin Bertambah Lingkungan Rusak <a href="https://t.co/zx73tl2ZQ9">https://t.co/zx73tl2ZQ9</a>                                                                                                                                                                                               |
| pendukung wowo tuh gak mau baca maunya disuapin pake opini dari pemerintah padahal selama ini hilirisasi nikel lebih banyak dampak negatifnya saking regulasinya yg tidak bagus Dikritisi oleh pak Tom lembong malah ngamuk-ngamuk..tujuannya untuk Membenahi Regulasinya agar sesuai <a href="https://t.co/es7zWnCp3D">https://t.co/es7zWnCp3D</a>              |

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#### AUTHOR CONTRIBUTIONS

Zulfitriah Kurniawan Mustafa: Concept development, research methods, data gathering, and analysis;

Anastasia Lidya Maukar: Project Administration, Data checking, Writing, Review, and Editing;

Galih Prakoso: Data gathering, and analysis; Rowan Abdelhaleem: Data gathering, and analysis.

#### CONFLICT OF INTERESTS

No conflict of interests were disclosed.

#### ETHICS STATEMENTS

Ethical approval was not applicable to this research since it did not involve human participants, animals, or sensitive data.

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