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Mapping Opinion Networks: An Interaction Network Analysis of Commenters on Narasi Newsroom's "Weda Bay Nickel Downstreaming" YouTube Video

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Abstract

Indonesia is the world's largest producer of nickel reserves. The government has implemented a nickel downstreaming policy to increase the added value of this commodity. One of the centres of nickel downstreaming is Weda Bay in North Maluku, which has recorded significant economic growth. Behind this financial success, nickel downstreaming has harmed social and environmental aspects. These impacts have triggered various responses from the community, many of which have been channelled through social media such as YouTube. This study analyses the network of public opinion in the comments section of the YouTube video "The Curse of Weda Bay Nickel Downstreaming (PART 1)" by Narasi Newsroom using the Social Network Analysis (SNA) method with Gephi 0.10 software and reviews negative, positive, and neutral sentiments using the Naïve Bayes model through Google Colab. The network analysis results show a diameter of 2, density of 0.000 (very low), and modularity of 0.838 (high), indicating that interactions between users are rare and that there are separate communities. Centrality measurements (degree, betweenness, closeness, and eigenvector) show @knowledgeid970 and @kadyrov12373 as the leading and most influential actors in the comment network. Naïve Bayes sentiment analysis shows that 52.49% of comments have negative sentiment, 26.45% are neutral, and only 21.06% are positive. The data needs to be balanced using SMOTE, and more accurate models need to be explored. Negative sentiment is dominated by concerns about environmental impacts such as deforestation, pollution, and pressure on clean water supplies due to nickel downstreaming.

Keywords: Naïve Bayes, Nickel, Sentiment, SNA, Weda, YouTube

Abstrak

Indonesia merupakan negara penghasil cadangan nikel terbesar di dunia. Pemerintah menerapkan kebijakan hilirisasi nikel untuk meningkatkan nilai tambah komoditas ini. Salah satu pusat hilirisasi nikel adalah Weda Bay di Maluku Utara, yang mencatatkan pertumbuhan ekonomi signifikan. Di balik keberhasilan ekonomi, hilirisasi nikel menimbulkan dampak negatif pada aspek sosial dan lingkungan. Dampak tersebut memicu berbagai respons dari masyarakat, yang banyak disalurkan melalui media sosial seperti YouTube. Penelitian ini menganalisis jaringan opini publik dalam kolom komentar video YouTube "The Curse of Weda Bay Nickel Downstreaming (PART 1)" oleh Narasi Newsroom menggunakan metode Social Network Analysis (SNA) menggunakan perangkat lunak Gephi 0.10 serta melihat sentimen negatif, positif, dan netral dengan menggunakan model Naïve Bayes melalui Google Colab. Hasil analisis jaringan menunjukkan diameter 2, density 0.000 (sangat rendah), dan modularity 0.838 (tinggi), mengindikasikan jarang terjadi interaksi antar pengguna dan adanya komunitas terpisah. Pengukuran sentralitas (degree, betweenness, closeness, dan eigenvector) menunjukkan @knowledgeid970 dan @kadyrov12373 sebagai aktor utama dan paling berpengaruh dalam jaringan komentar tersebut. Analisis sentimen Naïve Bayes menunjukkan bahwa 52.49% komentar memiliki sentimen negatif, 26.45% netral, dan hanya 21.06% positif. Data perlu diseimbangkan menggunakan SMOTE dan perlu mengeksplorasi model lain yang lebih akurat. Sentimen negatif didominasi oleh kekhawatiran terhadap dampak lingkungan seperti deforestasi, pencemaran, dan tekanan pada pasokan air bersih akibat hilirisasi nikel.

Kata kunci: Naïve Bayes, Nikel, Sentimen, SNA, Weda, YouTube

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INTRODUCTION

According to the U.S. Geological Survey (2024), Indonesia is the world's largest nickel producer, with production reaching 1.58 million tons in 2022 and increasing to 1.8 million tons in 2023. In addition, Indonesia also has the world's largest nickel reserves, amounting to approximately 55 million tons, far surpassing other countries such as Australia and Brazil. The distribution of nickel in Indonesia is mainly found in the Sulawesi Islands, Kalimantan, Maluku, Halmahera Islands, and Papua. Nickel is a metal element that is often found in the earth's crust and is needed by many industries, one of which is the stainless steel industry, which is widely used for household appliances, construction, and transportation (Radhica & Wibisana, 2023). This position makes Indonesia strategically crucial in the global nickel supply chain, particularly for the needs of stainless steel and electric vehicle batteries. With such potential, Indonesia is poised to be a key player in the world's energy transition, a promising prospect for the country and the global community.

Nickel was initially imported in the form of nickel ore before the ban on raw mineral exports, so the utilization of nickel in Indonesia is still minimal. With the utilization that has not been maximized, the government is taking proactive steps to increase the exchange value of nickel ore by processing it into products that have a higher selling value, which is called nickel downstreaming. Downstreaming is one of the government's strategies to boost the national economy and optimize the utilization of natural resources. One of the leading centers for nickel downstreaming is Weda Bay, a nickel mining complex and industrial area located in the Central Weda District, Central Halmahera Regency, North Maluku. This industrial area is known as the Indonesia Weda Bay Industrial Park (IWIP). For the economy, nickel-down streaming recorded an economic growth of 13.73% in the Gross Regional Domestic Product (GRDP) in North Maluku in the fourth quarter of 2024. Through this achievement, North Maluku managed to record the highest economic growth in Indonesia in 2024. However, amidst the success of downstreaming in terms of employment and economy, there are negative impacts on social and environmental aspects in the surrounding area.

Efforts to downstream nickel require ample natural resources, especially related to land, transportation access, and high volumes of water. As a result, massive environmental and social changes will occur. Various impacts caused by nickel mining are deforestation (loss of land cover in the form of forests), water pollution, air pollution, changes in the livelihood patterns of residents, and damage to flora and fauna habitats around the mining area (Saputra et al., 2023). The existence of positive and negative impacts associated with nickel downstreaming has led to various responses from the community. The reactions shown by the community can be in the form of verbal and nonverbal responses. Public responses can now be disseminated through various media, including social media.

According to Boyd (2015), social media is a collection of software that allows an individual or community to gather, share information, and communicate with each other on a particular issue (Nasrullah, 2015). The existence of various social media with different characteristics allows users to express themselves by creating video and audio content. One of the media that can be used to disseminate video content is YouTube. YouTube is not only a source of entertainment and information, but also an interactive space where two-way communication takes place between creators and users, or even between users themselves. Features such as comment sections, like buttons, video sharing, and channel subscriptions strengthen YouTube's role as a social media platform that encourages active user participation. According to (Benevenuto et al., 2008), YouTube social networks are formed through video interactions between users, with typical user behavior patterns and evidence of anti-social behavior. The dynamics of anti-social behavior can structure and influence the quality of discussions within the network. In addition, YouTube's video response feature reveals common patterns of user behavior and opportunistic behavior in online video social networks(Benevenuto et al., 2009).

Social Network Analysis (SNA) examines the relationships (edges) between social entities (nodes), such as individuals or organizations, to understand how these connections affect behavior and outcomes (Tabassum et al., 2018). When members of a network seek information, they often refer to other network members, thereby forming a social network pattern. Individuals in the network are bound to each other, and the relationship of individual roles in this network system will determine who is an influential actor and has a leading role in the social network. There are four levels in network analysis, namely nodes, components, and complete networks (Prell, 2012). The relationship between nodes in a network can be represented through a graph theory approach. This theory is a method for studying networks of all types of fields (Joviansyah et al., 2023). In graph theory, a visualization of the relationship diagram of a social network is provided. This diagram consists of nodes (points) and edges (lines) that will be connected. Nodes are actors or network members, which are usually individuals or organizations. Meanwhile, edges or lines are points and social relationships that exist between nodes. In Social Network Analysis, there is a core concept used to determine the center point of a network, namely degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality (Habibi & Sunjana, 2019).

The SNA method produces patterns of interaction between related actors, but cannot assess the text or message being conveyed. Therefore, sentiment analysis is needed to identify texts from different opinions. According to Boro et al. (2025), sentiment analysis is the process of gathering public opinion on a topic under discussion. These opinions are then classified into three sentiment categories: positive, negative, and neutral. The integration of these two approaches provides a conceptual framework to explain how the issue of nickel downstreaming is debated, how public sentiment is formed, and how the discourse spreads and is structured in YouTube comments. The research by Wijaya et al. (2024) states that SNA can create visualizations and feedback to improve practices, so that it not only focuses on exploring relationships and structures within the formed network. That is in line with their research literature review, which cites Clark-Ginsberg et al. (2022) stating that the value of SNA lies in understanding how government governance policy-making networks are formed, from complex and intricate processes involving many stakeholders working together and competing with each other. Meanwhile, sentiment analysis can shape communication and collaboration between interested parties, including the government, companies (such as nickel), and the general public, to achieve mutually beneficial goals (Rauf, 2023). This statement is relevant to the issue of nickel downstreaming because it can show how public debate on the policy is formed, which actors are most influential in spreading narratives, and how public sentiment can influence the legitimacy and direction of policies taken by the government.

Research by Shajari et al. (2023) with the title "Commenter Behavior Characterization on YouTube Channels" uses the SNA method to detect gangs of commenters who collaborate to increase specific engagements. As a result, there is evidence of coordinated suspicious activity on

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these channels, which explains the behavior of the inter-commentator community. Furthermore, the study "Examining Information Diffusion Patterns in YouTube Comment Networks, A Social Network Analysis Approach" by Nanayakkara et al. (2024) analyzed the patterns of information diffusion in networks formed from comments on YouTube and who the key actors involved in information dissemination are. Merdiansah et al. (2024) also researched X user sentiment analysis related to electric vehicles. Of the two studies, the objects used include several YouTube videos with various topics, but no research focuses on the issue of nickel downstreaming. Therefore, this study will explore the comments on the video "The Curse of Weda Bay Nickel Downstreaming (PART 1) | Buka Mata" on the Narasi Newsroom YouTube channel. Although the title suggests the video is part 1, it does not have a continuation. This video raises issues that have multiple dimensions, not only related to macroeconomic aspects such as foreign exchange and investment, but also concerning the socio-economic conditions of local communities, labor dynamics, and the environmental impact of industrial activities. Through an investigative documentary format, this video presents a critical narrative of downstreaming practices, including the potential imbalance between the enormous profits earned by companies and the vulnerability experienced by surrounding communities. Its significance is further amplified by the fact that the video was published on a digital platform, enabling it to reach a broad audience while also sparking open discussion in the comments section. The sentiment analysis model used the Naïve Bayes classifier, which is a probabilistic-based method to classify text such as positive, negative, or neutral. This algorithm estimates the probability of a text belonging to a particular sentiment class by analyzing the frequency of words from the training dataset. Furthermore, this research aims to see the connections between individuals that form a communication network and how public sentiment is constructed.

RESEARCH METHOD

This study uses the Social Network Analysis (SNA) method with a complete network design and Naïve Bayes classifier to analyze sentiment. SNA method is used to visualize the structure of the information and identify key actors in a network. That also provides information related to the structure and patterns of networks formed between actors. The data processing in this study was performed by collecting data using the web-based application labs.polsys.net, which was then processed using Gephi version 0.10.1, thereby revealing the interaction patterns within the network. The dataset consists of 1,279 nodes and 393 edges, representing the total text comments and their interaction structure. According to graph theory, there are two stages of analysis conducted in accordance with the research objectives. The first stage involves analyzing the network structure, including the type, patterns, and relational connections formed in the comment section of the video "The Curse of Weda Bay Nickel Downstreaming (PART 1) | Buka Mata" on the Narasi Newsroom YouTube channel. The second stage is the analysis of key actors through actor centrality, namely degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality (Mulyani et al., 2022). Degree Centrality is a calculation of the popularity of actors in a social network or the number of relationships to and from actors. Closeness Centrality is a calculation of the proximity of one actor to another. Betweenness Centrality is a calculation used to determine which actors are influential and act as intermediaries within the network. Meanwhile, Eigenvector Centrality is used to find the most important actors by identifying the influence of their accounts on the entire network (Bakry, 2023).

Then, sentiment analysis was processed using the Naïve Bayes classifier model through Google Colaboratory. Previous research by Albab et al. (2024) showed that Naïve Bayes has a higher accuracy than other classification methods, which amounted to 84%. Rauf's (2023) research on mining sentiment analysis also used the Naïve Bayes algorithm, which classified sentiment with an accuracy rate of 85% and a precision rate of 83.5%. This research shows that Naïve Bayes is capable of achieving a high level of accuracy even though the data used was biased towards negative sentiment. The sentiment analysis process begins with data crawling, which involves collecting comments from the YouTube platform using the YouTube Data API v3. This stage produces a collection of comments that are then further processed through a series of pre-processing steps. The first step is data cleaning to remove irrelevant elements such as punctuation marks, numbers, URLs, and symbols. Next is tokenization, which breaks sentences into word units for easier analysis. The following process involves removing common words or high-frequency stop words that do not contribute significantly to meaning, as well as stemming to return words to their basic form to ensure consistency. After this stage, comments are labelled as positive, negative, or neutral sentiment, then represented numerically using the TF-IDF method, which weights words according to their level of importance. The sentiment analysis stage is carried out using the Naïve Bayes model. To manage the imbalance in the distribution of comments, data balancing was performed using SMOTE (Synthetic Minority Over-sampling Technique) to improve the representation of minority classes. The model is then evaluated using test data. The F1-score value provides a more accurate picture of the model's performance in unbalanced data conditions. Further evaluation was carried out through a confusion matrix, which shows patterns of correct and incorrect classifications.

RESULTS AND DISCUSSION

From the analysis conducted on the YouTube video “The Curse of Weda Bay Nickel” on the Narasi Newsroom YouTube channel, the following findings were collected.

Figure 1. Screenshot of Narasi Newsroom YouTube broadcast (Source: YouTube (2024))

Table 1. Information about Narasi Newsroom YouTube videos

Video ID	rg698JD-F5Y
Account Name	Narasi Newsroom

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Title	The Curse of Weda Bay Nickel Downstreaming (PART 1) | Buka Mata
Upload Date	September 18, 2024
Number of Views	714.443
Number of Likes	11.000
Number of Comments	2.959
Description	Hilirisasi nikel adalah jargon yang terus-menerus dilontarkan Presiden Joko Widodo. Program itu kerap dikaitkan dengan energi hijau dan transisi kendaraan listrik, seperti yang belakangan gencar disampaikan pemerintah. Namun, apakah hilirisasi ini betul-betul hijau? Di Halmahera Tengah, hutan terus ditebang dari tahun ke tahun untuk industri nikel. Beberapa tahun terakhir, angka deforestasi melesat tajam. Kami menelusuri Teluk Weda, melihat langsung bagaimana industri nikel berjalan. Temuan kami: air Sungai Sagea tercemar logam berat, diduga karena aktivitas nikel di wilayah hulu. Air sungai yang sejak dulu adalah sumber kehidupan warga, kini sulit dimanfaatkan. Industri nikel membuat penduduk sengsara. Di Desa Lelilef, warga mesti terpapar debu yang disebabkan aktivitas perusahaan. Mereka hidup berdampingan dengan kompleks PT Indonesia Weda Bay Industrial Park (IWIP). Dampak lain sejak kehadiran perusahaan: air tanah menjadi asin, nelayan juga kian sulit mendapatkan ikan. Belum lagi banjir besar yang menerjang Teluk Weda pada 21 Juli 2024. Diduga, perusahaan ikut andil menyebabkan bencana ini. (Narasi)

Analysis results show that this YouTube comment network has a diameter of 2, meaning that the farthest distance between two nodes (users) in the network is only two steps. In other words, every user in the network can reach another user through a maximum of two direct or indirect connections. The density value of 0.000 is classified as very low, indicating that interactions between users in the network are infrequent. Meanwhile, the modularity value of 0.838 places in the high category, indicating that the network is divided into communities or small groups that are fairly separate from one another.

Degree Centrality

Table 2. Degree Centrality (Source: Gephi (2025))

No.	Actors	Degree	In-degree	Out-degree
1	@knowledgeid970	35	34	1
2	@HR-rw1uf	34	33	1
3	@Hombing-j5p	33	33	0
4	@dhimassahidpangestu3139	29	29	0
5	@priscillatarigany	27	26	1

From the table above, it can be seen that the top 5 actors are ranked from highest to lowest degree. The account @knowledgeid979 is the actor with the highest degree, which is 35. This shows that @knoeledgeid970 is the most popular actor in the comments section of the YouTube video "The Curse of Weda Bay Nickel Downstreaming" with 35 connections. Next, in second place is the account @HR-rw1uf with 34 connections, followed by the account @Hombing-j5p with 33 connections, fourth place is the account @dhimassahidpangestu3139 with 29 connections, and in last place is the account @priscillatarigany with 27 connections. The table also shows the in-degree and out-degree values for each account (actor) in the comments section of the video "The Curse of Weda Bay Nickel Downstreaming." Actors with high in-degree values indicate that their comments are frequently replied to, while out-degree values indicate how often the actor replies to others' comments (Utami et al., 2021). The account @knowledgeid979, which has the highest degree value of 35, has an in-degree value of 34 and an out-degree value of 1. Meanwhile, the account @priscillatarigany, which has the lowest degree value of 27, has an in-degree value of 26 and an out-degree value of 1. As shown in the table above, not all actors reply to comments, so actors (accounts) like @Hombing-j5p and @dhimassahidpangestu3139 have an out-degree value of 0.

Figure 2. Degree Centrality (Source: Gephi (2025))

Betweenness Centrality

Table 3. Betweenness Centrality (Source: Gephi (2025))

No.	Actors	Betweenness
1	@kadyrov12373	0.000013
2	@batagorcahbrebss7914	0.000007
3	@TengkuPangeran	0.000002
4	@uluelangarun99	0.000002
5	@FitraFit-uz1wp	0.000001

The following analysis is on betweenness centrality. This analysis aims to identify influential actors within a network and determine the position of nodes as intermediaries of information from one actor to another. The betweenness centrality coefficient ranges from 0 to 1. Actors with high betweenness centrality values are considered key actors because they act as connectors between groups with different networks and can control and manipulate the information conveyed. In the table above, the five accounts (actors) with the highest betweenness centrality values are @kadyrov12373, @batagorcahbrebss7914, @TengkuPangeran, @uluelangarun99, and @FitraFit-uz1wp. The highest betweenness centrality value is found in the account @kadyrov12373 with a value of 0.000013, followed by the second-highest value in the account @batagorcahbrebss7914 with a value of 0.000007. The accounts @TengkuPangeran and @uluelangarun99 have the same betweenness centrality value of 0.000002, while the account @FitraFit-uz1wp has the lowest betweenness centrality value in the sequence, at 0.000001. Among these five accounts, the betweenness centrality values are less than 1, indicating that the actors in the comments section of the video “The Curse of Weda Bay Nickel Downstreaming” rarely engage in interactions.

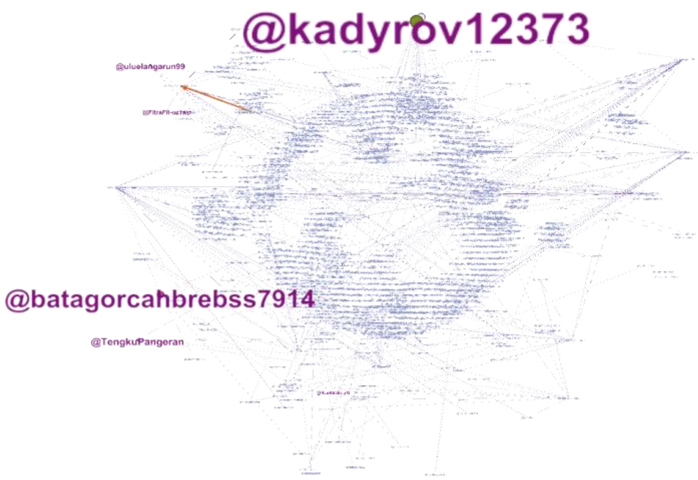

Figure 3. Betweenness Centrality (Source: Gephi (2025))

Closeness Centrality

Table 4. Closeness Centrality (Source: Gephi (2025))

No.	Actors	Betweenness
1	@kadyrov12373	0.000013
2	@batagorcahbrebss7914	0.000007
3	@TengkuPangeran	0.000002
4	@uluelangarun99	0.000002
5	@FitraFit-uz1wp	0.000001

Closeness centrality is used to determine the average distance between nodes or actors in a network to measure the closeness of these actors with a coefficient in the range of 0-1. Closeness centrality will affect the dissemination of information. In the table above, it can be seen that in the YouTube video comment network titled “The Curse of Weda Bay Nickel Downstreaming,” there are five actors with a closeness centrality value of 1.0, indicating that these actors are closely connected to other actors. These accounts include @kadyrov12373, @batagorcahbrebss7914, @Nurul-lb5ml, @uluelangarun99, and @TengkuPangeran. According to Utami et al. (2021), as the closeness centrality value approaches 1, the actor becomes closer to other actors within the network.

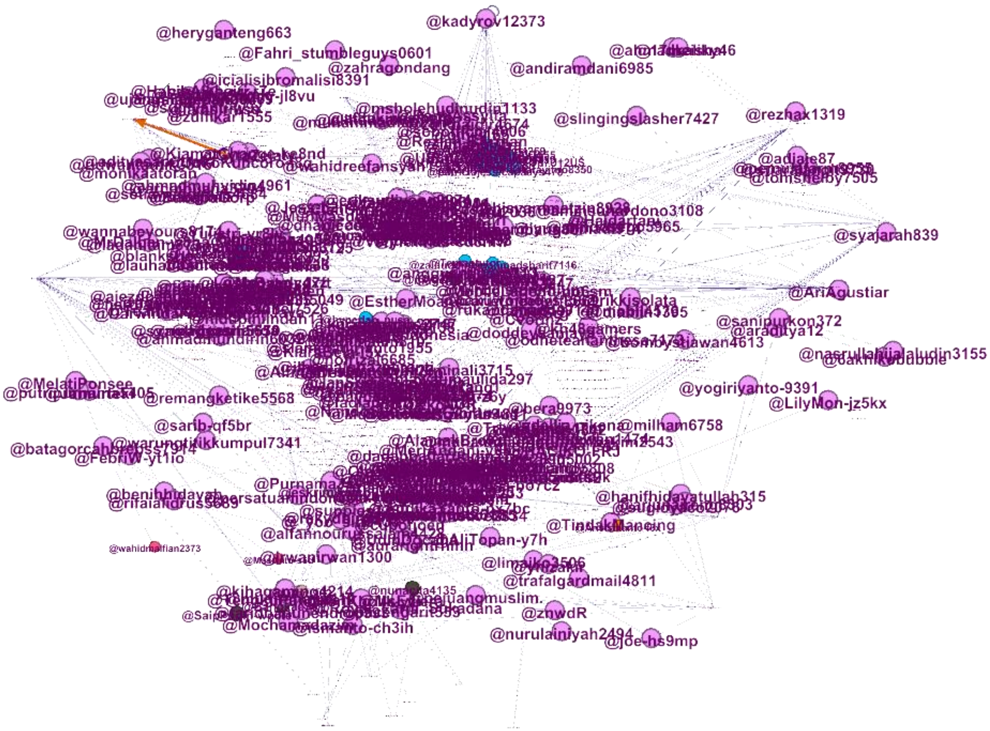

Figure 4. Closeness Centrality (Source: Gephi (2025))

Eigenvector Centrality

Table 5. Eigenvector Centrality (Source: Gephi (2025))

No.	Actors	Eigenvector
1	@knowledgeid970	1.0
2	@HR-rw1uf	0.99248
3	@priscillatarigany	0.83038
4	@kadyrov12373	0.04166
5	@ZainalAbidin-jg9zh	0.00757

Based on the analysis in the table above, it can be seen that the actor @knowledgeid970 obtained an eigenvector centrality value of 1.0. This means that this actor has relationships with many important actors in the YouTube comment network on the video "The Curse of Weda Bay Nickel Downstreaming," so it can be said that the actor @knowledgeid970 is a key actor in the formation of the video network.

Figure 5. Eigenvector Centrality (Source: Gephi (2025))

The finding of very low network density (0.000) indicates that interactions between users in YouTube comment sections are fragmented, with small direct connections between accounts. This is consistent with the findings of Kumar et al. (2018), which show that online discussions on platforms such as YouTube resemble public monologues rather than dialogues, as users tend to express personal opinions without engaging in layered conversations. On the other hand, the high modularity value (0.838) in YouTube comments points to the formation of distinct, separate communities. This finding, consistent with Garimella et al. (2018) research, suggests that issue polarization on social media reinforces the echo chamber effect. Interactions are more frequent within groups that share similar opinions, rather than across diverse groups. Therefore, high modularity in YouTube comments is a reflection of the polarization of environmental discourse. In addition, the very low betweenness centrality (close to zero) in almost all nodes shows the absence of dominant actors who function as bridges between communities. This phenomenon is in line with the findings of Dubois & Blank (2018), which show that in digital discourse, the role of information brokers rarely emerges organically, so that the flow of information tends to be trapped within the internal circles of each community. The implication is that opportunities for cross-view dialogue become limited, and polarization intensifies.

Sentiment Analysis

In this study, 2,631 comments were successfully analyzed, which is considered to represent all comments. YouTube comment analysis was not conducted on all the comments because access to comments through the YouTube API is limited by daily quotas and usage rules set by Google. The results of the sentiment analysis on the YouTube video comments for “The Curse of Weda Bay Nickel Downstreaming” produced the following sentiment distribution.

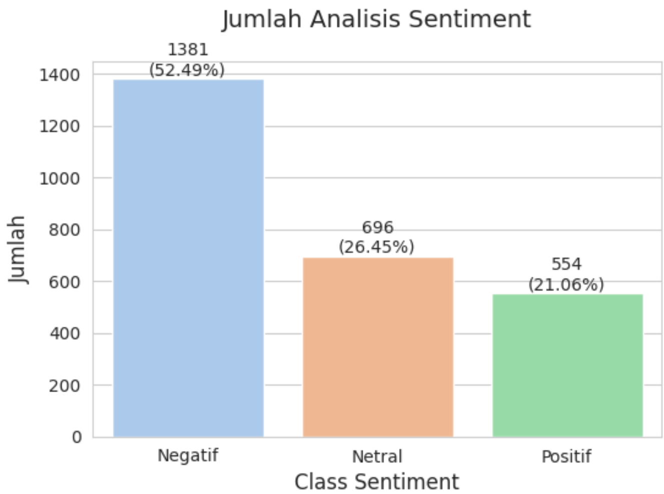

Figure 7. Sentiment distribution (Source: Google Colab (2025))

Negative sentiment accounted for the most considerable portion of the data generated, at 52.49%. This indicates that most texts and reviews expressed dissatisfaction, criticism, or views opposing the nickel downstreaming policy, primarily due to the environmental impact of smelters. Meanwhile, 26.45% of the data had neutral sentiment. These texts likely contain facts, information without strong emotions, or ambiguous expressions that cannot be categorized as positive or negative. The proportion of positive sentiment is the smallest, at only 21.06%. This means that only a small portion of the data expresses satisfaction, support, or positive views toward the nickel downstreaming policy, which is believed to boost the economy.

The high proportion of negative comments on the video The Curse of Weda Bay Nickel Downstreaming (PART 1) | Buka Mata cannot be separated from the context of nickel downstreaming, which is fraught with controversy. The nickel industry in the Weda Bay region is

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often associated with environmental damage, water and air pollution, and the loss of local communities' living spaces. Setiawan & Fadlhia (2025) state that nickel downstreaming projects reveal tensions between commitments to a green economy and the reality on the ground, which often poses risks to the environment and social justice, in the form of pollution by the corporation PT. IWIP in the community of Central Halmahera Regency consists of river water pollution, soil contamination, and air quality pollution originating from manganese and nickel mining activities in Central Halmahera Regency (Bidul & Widowaty, 2024). This situation has shaped public perception that downstreaming benefits large corporations and foreign investors more, while the surrounding community bears the socio-ecological burden. The critical narrative presented in the video further strengthens the audience's tendency to express negative sentiments through comments, whether in the form of protests, anger, or sarcasm. Meanwhile, neutral comments come from users who tend to take a cautious stance by only asking questions or adding information without showing emotional attitudes. Positive comments are fewer because, in the context of nickel, optimism or support is often less dominant than concerns about the real impacts felt by the community. This distribution of sentiment illustrates how digital media can be a space for public criticism of the state's strategic policies, while also reflecting mistrust and disappointment with downstreaming practices that are considered not to fully support local interests or environmental sustainability. The subtle difference between positive and neutral sentiment can be influenced by sarcastic comments. Sarcasm often uses words that appear favourable, but are actually meant to be critical. This significant role of sarcasm contributes to the emergence of a proportion of positive sentiment that is almost balanced with neutral sentiment, even though criticism still dominates the discourse in substantive terms.

Figure 6. Sentiment word cloud (Source: Google Colab (2025))

Public negativity is also evident in Rajani & Hasugian (2025) study on nickel mining plans in Raja Ampat, which sparked fierce resistance due to threats to the marine ecosystem and biodiversity. This confirms that the higher the ecological value of an area, the stronger the public resistance to extractive activities. In the context of corporate communication, Fahmi et al. (2021) show that the image of mining companies in Indonesia, such as PT Freeport, is often disrupted by negative sentiment on social media due to weak communication management and a lack of response to public criticism. It means that, in addition to environmental factors, the inability of mining actors to manage public discourse also contributes to the dominance of negative sentiment. Furthermore, Kurniawan et al. (2021) emphasize that despite the environmental programs implemented by nickel smelter companies, the community continues to hold negative perceptions because they do not feel any direct benefits. Thus, the concrete experiences of local communities, not just policy narratives, also play a significant role in shaping public opinion.

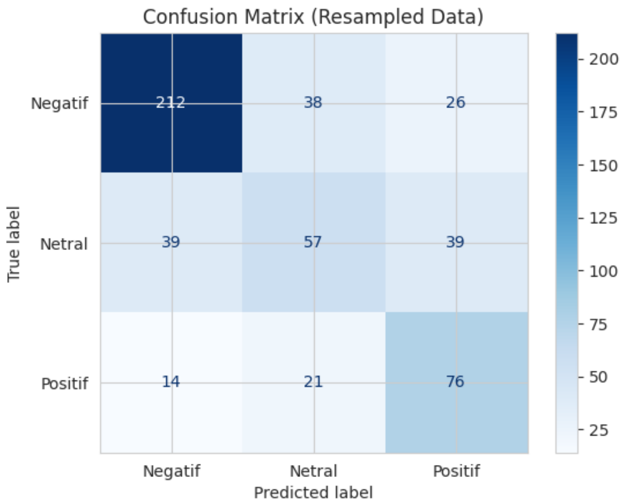

Figure 7. Confusion matrix (Source: Google Colab (2025))

The Naïve Bayes model was trained with training data resampled using SMOTE. Data balancing was performed because the distribution of comments in each sentiment class was unbalanced. If the data remained unbalanced, the model would tend to be biased toward the dominant class and ignore the minority class. By using SMOTE, the class distribution was made more proportional so that the model had the same learning opportunity for each sentiment category, and the prediction results became more representative. The evaluation results of the Naïve Bayes model after data balancing with the SMOTE method showed an accuracy rate of 66.09%, with relatively balanced precision, recall, and weighted F1-score, each in the range of 0.66. This value indicates that the model's performance is at a moderate level, so that it can classify sentiment quite nicely despite its limitations. The confusion matrix suggests that the model struggles to distinguish between neutral and positive or negative sentiment, as evidenced by the high number of misclassifications. For instance, 47 neutral comments were incorrectly predicted as negative, and 39 neutral comments were incorrectly predicted as positive. Similarly, positive sentiment is often mistaken for negative or neutral, and some negative comments are predicted as other classes. This condition shows that even though SMOTE helps balance class distribution, the Naïve Bayes model still has limitations in capturing the complex nuances of language in comments, especially for neutral sentiment, which is often more ambiguous and challenging to identify consistently.

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CONCLUSION

Through the YouTube video "The Curse of Weda Bay Nickel Downstreaming" a communication network was found in the comments section with 1,279 nodes and 393 edges. The diameter value was 2, the density was 0.000, and the modularity was 0.838. To identify the actors involved and influential in the comment network, centrality measurements were conducted using the following indicators: degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. The analysis revealed that the actors @knowledgeid970 and @kadyrov12373 are the leading and most influential actors, as both actors consistently achieved the highest centrality scores compared to other actors in the network. Negative sentiment, with a substantial score of 52.49%, was the most prevalent. The word cloud's focus on issues such as mining, the environment, the people, and the government underscores these prevalent concerns and can guide future research in sentiment analysis. Despite the Naïve Bayes model's enhanced performance post-SMOTE, there is still room for improvement. The model's significant misclassification between classes indicates a need for further development to better capture the nuances of sentiment in text. The disparities in the outcomes of lexicon analysis and machine learning models present an intriguing area for future investigation. This comparison could yield valuable insights and stimulate further research in sentiment analysis.

The results of this study open up strategic opportunities for stakeholders to manage environmental discourse related to nickel downstreaming more effectively. For the government, the dominance of negative sentiment indicates the need for greater transparency in explaining the benefits of downstreaming, accompanied by concrete steps to address social and ecological impacts. Utilizing actors with high eigenvector and betweenness centrality values can be an efficient communication channel, as these actors serve as opinion bridges between clusters and have an influence in strengthening the legitimacy of government messages. Meanwhile, the media has an essential role in managing public narratives by avoiding the dominance of a single discourse that only emphasizes economic benefits. By employing SNA findings, the press can identify sensitive topics in the public sphere and provide more balanced coverage, including highlighting the experiences of local communities directly affected by mining activities. Thus, integrating sentiment analysis and SNA findings can help stakeholders not only understand patterns of public perception but also design more targeted communication and intervention strategies to minimize conflict and build policy legitimacy. Further research is not just suggested, but crucial, to expand the scope of analysis by comparing patterns and public perceptions across various social media platforms, such as Twitter, Facebook, or TikTok, so that variations in discourse between the national and local spheres can be observed. After identifying that the accuracy of the Naïve Bayes model is insufficient, further research can also focus on exploring other machine learning models that are more complex and have the potential to deliver better results.

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