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Research Article

Sentiment Classification and Influential Actor Detection on Twitter (Case Study: The Raja Ampat Mining Conflict)

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Abstract:
The nickel mining conflict in Raja Ampat has attracted extensive public attention due to the region's global ecological significance and the potential environmental risks posed by extractive activities. Social media platforms, particularly Twitter, have become important spaces for public discussion and opinion exchange regarding this issue. This study aims to analyze public sentiment and identify influential actors in online discussions of the Raja Ampat mining conflict by integrating sentiment analysis and Social Network Analysis (SNA). This study adopts a cross-sectional design using Indonesian-language tweets collected between 15-27 November 2025. A total of 11,671 tweets were obtained through keyword-based crawling, and after preprocessing and duplicate removal, 8,909 tweets were retained for analysis. Sentiment labeling was performed using a *lexicon-based* approach, categorizing tweets into positive, neutral, and negative classes. The dataset was divided using an 80:20 train–test split. Sentiment classification was conducted using Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naive Bayes algorithms. Model performance was evaluated using *confusion matrix–based* metrics, including accuracy, precision, recall, and F1-score. Social Network Analysis was carried out by constructing a directed interaction network based on mentions, replies, and retweets, with influential actors identified using degree and betweenness centrality measures. The results indicate that neutral sentiment dominates the discourse (51.58%), followed by negative and positive sentiments. SVM and Naive Bayes demonstrate more stable classification performance than KNN, while network analysis shows that influence is concentrated among a limited number of central actors.

Keywords: Sentiment Analysis, Social Network Analysis, SVM, KNN, Naive Bayes, Nickel Mining, Raja Ampat, Twitter.

1. Introduction

The mining case in Raja Ampat has attracted widespread public attention in Indonesia, as the region is internationally recognized as one of the world's most important marine biodiversity hotspots [1]. Concerns regarding the potential environmental impacts of mining activities on this fragile ecosystem have triggered intense public debate, particularly on social media platforms. Social media functions as a primary arena for opinion formation, argument exchange, and influence dissemination among actors involved in environmental conflicts. Therefore, systematic analysis of online discourse is essential to understand public sentiment dynamics and the structure of influence that emerges within such debates.

Previous studies have combined sentiment analysis and Social Network Analysis (SNA) to examine public opinion and identify influential actors on social media [2]. However, many of these studies remain generic, focusing mainly on sentiment proportions and basic centrality measures without deeply contextualizing the findings within specific environmental conflicts. In the context of mining issues in Raja Ampat, empirical studies that explicitly link sentiment dynamics, local environmental concerns, and actor roles within communication networks are still limited. This gap indicates the need for domain-specific analysis that integrates sentiment patterns with network-based actor identification [3].

In addition, classical machine learning algorithms such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naive Bayes are widely applied in sentiment classification tasks [4]. Nevertheless, comparative evaluations are often conducted using inconsistent experimental settings, particularly with respect to feature representation, data splitting strategies, and evaluation metrics. Such inconsistencies hinder the interpretability of results and limit meaningful comparisons across studies. This research addresses this issue by applying a transparent and consistent experimental protocol to compare the performance of the three algorithms on the same dataset [5].

Based on these considerations, this study aims to: (1) analyze the distribution and expression of public sentiment related to mining issues in Raja Ampat on social media; (2) identify influential actors based on the structural characteristics of the communication network; and (3) compare the performance of SVM, KNN, and Naive Bayes using consistent feature representations, training–testing strategies, and evaluation metrics [5]. The study does not assume the superiority of any particular model or sentiment orientation, but derives conclusions solely from empirically validated results.

The main contributions of this research are threefold. First, it provides domain-specific insights into public discourse surrounding mining activities in Raja Ampat. Second, it strengthens social network analysis by reporting more comprehensive network characteristics for actor identification [3]. Third, it offers a methodologically consistent comparative evaluation of classical machine learning algorithms for sentiment classification, thereby supporting reproducibility and interpretability in applied data science research.

2. Method

This study adopts a cross-sectional time design, where data were collected within a defined observation period. The research focuses on Indonesian-language tweets related to the nickel mining issue in Raja Ampat. The methodological workflow consists of data collection, relevance filtering, text preprocessing, sentiment labeling, sentiment classification modeling, and Social Network Analysis (SNA), followed by result interpretation [6].

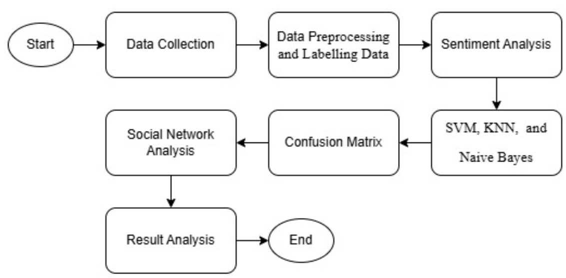

Figure 1: Research Methodology

Tweet data were collected from the X (Twitter) platform using the Crawling via Python during the period from June 2025 to November 2025. The data collection query used a predefined set of Indonesian keywords related to mining activities and environmental conflicts, including nickel mine, Raja Ampat, mining, gold mine, sand mine, illegal mining, mining permit, case, scandal, protest, rejection, conflict, controversy, community, residents, fishermen, activists, environmental actors, government, and companies [7].

To ensure data relevance, several filtering rules were applied. First, duplicate tweets were removed based on identical text content. Second, non-relevant tweets that did not explicitly refer to mining activities or environmental conflict contexts were excluded through manual keyword relevance checks [8]. Retweets were retained only when they contributed to interaction analysis for SNA, while bot-like accounts were filtered out using heuristic rules such as unusually high posting frequency and identical repetitive content. These steps were applied to improve data quality and analytical validity [3].

Text preprocessing was conducted to standardize and clean the tweet corpus prior to analysis. The preprocessing pipeline included text cleaning (removal of URLs, mentions, hashtags symbols, numbers, and punctuation), case folding (lowercasing), slang word normalization using an Indonesian slang dictionary, stopword removal based on the Indonesian stopword list, tokenization, and stemming using the Sastrawi library [9]. Tweets with empty or extremely short content after preprocessing were excluded. The cleaned and normalized dataset was then prepared for sentiment analysis and network construction. Sentiment labeling was performed using a lexicon-based approach [10]. A positive and a negative sentiment dictionary were constructed from commonly used Indonesian sentiment terms that appeared in the preprocessed corpus. Each tweet was assigned a sentiment score by summing the polarity values of sentiment-bearing words contained in the tweet [11]. Tweets with a positive total score were labeled as positive, tweets with a negative total score were labeled as negative, and tweets with a score of zero were labeled as neutral. This automated labeling process was implemented in Python and executed in the Google Colab environment to ensure reproducibility [12].

For sentiment classification, the textual data were transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF–IDF) representation [13]. Three machine learning algorithms were evaluated: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naive Bayes (NB). The SVM model employed a linear kernel with the regularization parameter C set to its default value. The KNN classifier used Euclidean distance with a predefined number of neighbors (k). The Naive Bayes classifier applied the Multinomial Naive Bayes variant, which is suitable for text-based features [14]. Model training and evaluation were conducted using an 80:20 train–test split, ensuring that the class distribution remained consistent across both sets [15].

Model performance was evaluated using a confusion matrix for each classifier. From the confusion matrix, standard evaluation metrics were calculated, including accuracy, precision, recall, and F1-score for each sentiment class [12]. These metrics were selected to provide a balanced evaluation, particularly given the potential class imbalance in sentiment data. Word cloud visualizations were also generated to highlight dominant terms associated with public sentiment regarding the Raja Ampat mining issue [16].

Social Network Analysis was conducted to examine interaction patterns among Twitter users involved in the discussion of the hashtag #tambangnikelrajaampat. An interaction network was constructed based on mentions, replies, and retweets, where nodes represent user accounts and edges represent interactions between users. Edge weights reflect interaction frequency, and the network was treated as a directed graph [17]. Centrality measures, including degree centrality, betweenness centrality, and closeness centrality, were calculated to identify influential actors, information brokers, and structurally central users [18]. Network visualization and modularity-based community detection were performed using Gephi, with node size and color scaled according to centrality values. The resulting network structure was interpreted to understand actor roles, information diffusion patterns, and the dynamics of public discourse surrounding the nickel mining conflict in Raja Ampat.

3. Result and Discussion

In sentiment analysis, the collected data from social media crawling is first processed through a text pre-processing stage to remove irrelevant elements. After that, sentiment is classified into positive, negative, or neutral using the Comparison of SVM, KNN, and Naive Bayes methods [1].

Data Collection

The data in this study were collected from the social media platform Twitter in the form of Indonesian-language tweets using the keyword "*tambang*" (mining). Data collection was conducted within the period from June 25, 2025, to November 31, 2025. The collected tweet data then underwent a preprocessing stage, which aimed to clean and prepare the data so that it would be ready for further analysis in subsequent stages [19]. The data crawling process in the Raja Ampat Nickel Mining study, which was conducted in a step-by-step and structured manner. First, the researcher input the Twitter/X access token (auth token) as an authentication key to enable authorized access to the API. After successful authentication, search keywords such as *"Raja Ampat nickel mining"*, *"Raja Ampat mining"*, or related hashtags were defined to filter relevant tweets [20]. Next, the crawling process was executed using Python to collect Indonesian-language tweets within the specified time range, including tweet text, date, and user information. The collected data were then stored in CSV format to facilitate data management and subsequent stages of preprocessing, sentiment analysis, and Social Network Analysis [17]. The data crawling results for the Raja Ampat mining case yielded 11,671 tweets, which were then used in the processing and sentiment analysis. **Table 1** presents the comment crawling results in **Table 1**.

Table 1. Data Crawling Results

NO	Created Time	Amount Like	Text	Number of replies	Amount retweet	User ID
1	ThuNov615:26:020”2025	0	*Warga Raja Ampat menolak rencana tambang nikel—ini ancaman bagi terumbu karang.*	0	0	1.88E+18"
2	ThuNov615:27:120”2025	2	*Apakah izin tambang nikel sudah melalui AMDAL yang transparan?*	0	5	1.97E+18"
3	ThuNov615:27:003”2025	3	*Protes besar-besaran hari ini menuntut moratorium tambang nikel di pesisir.*	0	8	1.97E+18"
	…..	…..	…..	…..	……	…..
11669	ThuNov615:27:180”2025	3	*gw smpek lupa letak aslinya gimana* 😭	1	0	6.90E+18”
11670	ThuNov615:27:180”2025	0	*kok penghentian sementara.. seharusnya di tutup selamanya lel bahlil*	0	0	6.93E+18”
11671	ThuNov615:27:130”2025	1	*#SAVERAJAAMPPAT*	0	0	7.23E+18”

Data Pre-processing

The pre-processing stage is the initial stage involving text mining to analyze text data and extract useful information. Through the application of text mining, an iterative process consisting of two main steps is carried out: structuring raw text data and then utilizing that data to extract relevant intelligence and insights [11]. The stages carried out in the data pre-processing process are explained as follows:

a. Delete Duplicate Data

To maintain data quality and accuracy during the analysis process, duplicate data was removed. Comments containing the exact same text were considered duplicate data. This process aims to eliminate repetitive comments to avoid redundancy and bias, particularly in sentiment analysis, which requires representative and unique data. This is expected to result in more valid and objective analysis results [13].

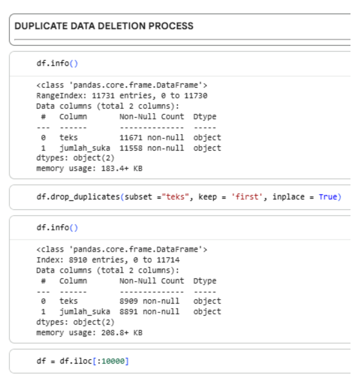

Figure 2. Delete Duplicate Data

Figure 2 shows that as many as 2762 words have been deleted from the initial 11671 words of comments, leaving 8909 words of clean data that can be used for further analysis to obtain better, more accurate and more reliable insights.

b. Data Cleaning

Data cleaning or data cleansing is the initial stage in text data processing which aims to remove irrelevant, inconsistent, or unimportant parts of the data so that the data becomes cleaner and ready for analysis.

Table 2. Cleaning

Text	Cleaning
Warga Raja Ampat menolak rencana tambang nikel...	*Warga Raja Ampat menolak rencana tambang nikel…*
Apakah izin tambang nikel sudah melalui AMDAL ...	*Apakah izin tambang nikel sudah melalui AMDAL .*
Protes besar-besaran hari ini menuntut morator...	*Protes besarbesaran hari ini menuntut moratori...*
Perusahaan mengklaim akan mempekerjakan warga ...	*Perusahaan mengklaim akan mempekerjakan warga ...*

Table 2 shows the results of data cleaning carried out on text data, including removing retweets, punctuation, mentions (@), URLs, irrelevant numbers, and other unnecessary special characters, so that the data becomes cleaner and ready to be used in the next analysis stage.

c. Case Folding

Case folding is one of the stages in text pre-processing that functions to change all characters in text data into lowercase letters, so that it can simplify the word identification process and increase data consistency in the next processing stage.

Table 3. Case Folding

Text	Cleaning	Folding Case
Warga Raja Ampat menolak rencana tambang nikel…	*Warga Raja Ampat menolak rencana tambang nikel…*	*warga Raja Ampat menolak rencana tambang nikel…*
Apakah ijin tambang nikel sudal melalui AMDAL…	*Apakah ijin tambang nikel sudal melalui AMDAL…*	*apakah ijin tambang nikel sudal melalui amdal…*
Protes besar-besaran hari ini menuntut morator…	*Protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*
Perusahaan mengklaim akan memperkerjakan warga…	*Perusahaan mengklaim akan memperkerjakan warga…*	*perusahaan mengklaim akan memperkerjakan warga…*

Table 3 shows the application of case folding, namely the process of changing all capital letters to lowercase letters as one of the pre-processing stages, with the aim of standardizing text data so as to facilitate the lexical analysis process in the next stage.

d. Word Normalization

Normalization is the process of standardizing words in comment text to conform to the standard word forms recognized in the Big Indonesian Dictionary (KBBI), so that it can improve the quality and accuracy of data in the analysis process.

Table 4. Word Normalization

Text	Cleaning	Folding Case	Normalization
Warga Raja Ampat menolak rencana tambang nikel…	*Warga Raja Ampat menolak rencana tambang nikel…*	*warga Raja Ampat menolak rencana*	*warga Raja Ampat menolak rencana tambang nikel…*

Text	Cleaning	Folding Case	Normalization
		tambang nikel…	
Apakah ijin tambang nikel sudal melalui AMDAL…	*Apakah ijin tambang nikel sudal melalui AMDAL…*	*apakah ijin tambang nikel sudal melalui amdal…*	*apakah ijin tambang nikel sudal melalui amdal…*
Protes besar-besaran hari ini menuntut morator…	*Protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*
Perusahaan mengklaim akan memperkerjakan warga…	*Perusahaan mengklaim akan memperkerjakan warga…*	*perusahaan mengklaim akan memperkerjakan warga…*	*perusahaan mengklaim akan memperkerjakan warga…*

Table 4 presents an example of how informal words are changed into more formal word forms to comply with KBBI guidelines.

e. Tokenizing

Tokenizing or tokenization is one of the stages in text pre-processing which aims to break down comment text into small parts in the form of words or certain units called tokens.

Table 5. Tokenizing

Text	Cleaning	Folding Case	Normalization	Tokenizing
Warga Raja Ampat menolak rencana tambang nikel…	*Warga Raja Ampat menolak rencana tambang nikel…*	*warga raja Ampat menolak rencana tambang nikel…*	*warga raja ampat menolak rencana tambang nikel…*	*[warga, raja, ampat, menolak, rencana, tambang, nikel]*
Apakah ijin tambang nikel sudal melalui AMDAL…	*Apakah ijin tambang nikel sudal melalui AMDAL…*	*apakah ijin tambang nikel sudal melalui amdal…*	*apakah ijin tambang nikel sudal melalui amdal…*	*[apakah, ijin, tambang, nikel, sudal, melalui, amdal]*
Protes besar-besaran hari ini menuntut morator…	*Protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*	*[protes, besar-besaran, hari, ini, menuntut, morator]*
Perusahaan mengklaim akan memperkerjakan warga…	*Perusahaan mengklaim akan memperkerjakan warga…*	*perusahaan mengklaim akan memperkerjakan warga…*	*perusahaan mengklaim akan memperkerjakan warga…*	*[Perusahaan, mengklaim, akan, memperkerjakan, warga]*

Table 5 shows the tokenization process, namely how text is separated and broken down into its smallest parts in the form of words or symbols, so that each component can be analyzed in a more structured manner at a later stage.

f. Stopword Removal

Stopword removal is carried out to eliminate words with less significant meaning, such as conjunctions and prepositions, so that the analysis can be more focused on relevant keywords. In this study, the list of stopwords used was sourced from the official NLTK corpus available in the stopwords package and accessed through the stopwords.words function.

Table 6. Stop Removal

Text	Cleaning	Folding Case	Normalization	Tokenizing	Stop Removal	Stop Removal
Warga Raja Ampat menolak rencana	*Warga Raja Ampat menolak*	*warga raja Ampat menolak*	*warga raja ampat menolak rencana*	*[warga, raja, ampat, menolak,*	*[warga, raja, ampat, menolak,*	*warga raja ampat tolak rencana*

Text	Cleaning	Folding Case	Normalization	Tokenizing	Stop Removal	Stop Removal
tambang nikel…	*rencana tambang nikel…*	*rencana tambang nikel…*	*tambang nikel…*	*rencana, tambang, nikel]*	*rencana, tambang, nikel]*	*tambang nikel…*
Apakah ijin tambang nikel sudal melalui AMDAL…	*Apakah ijin tambang nikel sudal melalui AMDAL…*	*apakah ijin tambang nikel sudal melalui amdal…*	*apakah ijin tambang nikel sudal melalui amdal…*	*[apakah, ijin, tambang, nikel, sudal, melalui, amdal]*	*[apakah, ijin, tambang, nikel, sudal, melalui, amdal]*	*ijin tambang nikel amdal transparan…*
Protes besar-besaran hari ini menuntut morator…	*Protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*	*[protes, besar-besaran, hari, ini, menuntut, morator]*	*[protes, besar-besaran, hari, ini, menuntut, morator]*	*Protes besarbesaran tuntut moratorium tambang…*
Perusahaan mengklaim akan memperkerjakan warga…	*Perusahaan mengklaim akan memperkerjakan warga…*	*perusahaan mengklaim akan memperkerjakan warga…*	*perusahaan mengklaim akan memperkerjakan warga…*	*[Perusahaan, mengklaim, akan, memperkerjakan, warga]*	*[Perusahaan, mengklaim, akan, memperkerjakan, warga]*	*Usaha klaim warga local…*

Table 6 illustrates the results of the stopword removal process, which shows the impact of editing the text by removing unimportant words, so that the text becomes more concise and focuses on the main information.

g. Stemming Data

The stemming process aims to convert words into their base forms by removing prefixes and suffixes. For example, the words *"pertambangan"* and *"pertambang"* are reduced to the base word *"tambang"*. In the case of *"pertambangan"*, the suffix *"-an"* is removed so that the word returns to its base form, *"tambang"*.

Table 7. Stemming Data

Text	Cleaning	Folding Case	Normalization	Tokenizing	Stop Removal	Stemming Data
Warga Raja Ampat menolak rencana tambang nikel…	*Warga Raja Ampat menolak rencana tambang nikel…*	*warga raja Ampat menolak rencana tambang nikel…*	*warga raja ampat menolak rencana tambang nikel…*	*[warga, raja, ampat, menolak, rencana, tambang, nikel]*	*[warga, raja, ampat, menolak, rencana, tambang, nikel]*	*warga raja ampat tolak rencana tambang nikel…*
Apakah ijin tambang nikel sudal melalui AMDAL…	*Apakah ijin tambang nikel sudal melalui AMDAL…*	*apakah ijin tambang nikel sudal melalui amdal…*	*apakah ijin tambang nikel sudal melalui amdal…*	*[apakah, ijin, tambang, nikel, sudal, melalui, amdal]*	*[apakah, ijin, tambang, nikel, sudal, melalui, amdal]*	*ijin tambang nikel amdal transparan …*
Protes besar-besaran hari ini menuntut morator…	*Protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*	*protes besar-besaran hari ini menuntut morator…*	*[protes, besar-besaran, hari, ini, menuntut, morator]*	*[protes, besar-besaran, hari, ini, menuntut, morator]*	*Protes besarbesaran tuntut moratorium tambang…*
Perusahaan mengklaim	*Perusahaan mengklaim*	*perusahaan mengklaim akan*	*perusahaan mengklaim akan*	*[Perusahaan, mengklaim,*	*[Perusahaan, mengklaim,*	*Usaha klaim warga*

Text	Cleaning	Folding Case	Normalization	Tokenizing	Stop Removal	Stemming Data
askan memperkerjakan warga…	*akan memperkerj akan warga…*	*memperkerjakan warga…*	*memperkerjakan warga…*	*akan, memperkerjakan, warga]*	*akan, memperkerja kan, warga]*	*local…*

Table 7 shows how words with the same root can be recognized.

Data Labelling

After all preprocessing stages are completed, the dataset then enters the data labeling stage, which will be used as training data. At this stage, the data is grouped into three sentiment classes: positive, neutral, and negative. A total of 8,909 data sets were used in the labeling process in this study [21].

Table 8. Sentiment

Stemming data	Score	Sentiment
warga raja ampat tolak rencana tambang nikel…	-3	*Negative*
izin tambang nikel amdal transparan…	0	*Neutral*
protes besarbesaran tuntut moratorium tambang…	-1	*Negative*
usaha klaim kerja warga lokal	1	*Positive*

Table 8 shows the results of the data labeling process, while the results are then visualized in the form of a diagram in **Figure 3** to facilitate understanding of the data distribution.

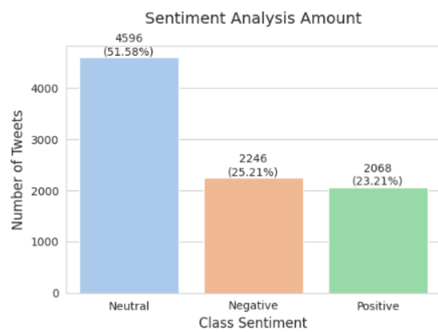

Figure 3. Class Sentiment.

Based on sentiment analysis results related to mining issues in Raja Ampat, there are three categories of sentiment: neutral, negative, and positive. Neutral sentiment dominated with 4,596 tweets (51.58%), indicating that most users simply conveyed information or opinions without a clear stance. Negative sentiment came in second with 2,246 tweets (25.21%), reflecting criticism and concern about the impacts of mining. Meanwhile, positive sentiment totaled 2,068 tweets (23.21%), generally expressing support and optimism toward mining activities [18].

a. Wordcloud

The sentiment analysis results were also visualized in a word cloud based on sentiment polarity: positive, negative, and neutral. Positive sentiment featured dominant terms such as "environment," "preservation," and "conservation," indicating support for Raja Ampat's protection efforts. Negative sentiment was dominated by terms such as "mining," "damage," and "threat," reflecting public concern about environmental impacts. These findings indicate that public discourse focuses primarily on environmental issues and opposition to mining activities in Raja Ampat [19].

Figure 4. Positive Wordcloud

Figure 5. Negative Wordcloud

Figure 6. Neutral Wordcloud

The following are the words that appear most frequently in each sentiment, which can be seen in the **Table 9** to **11**.

Table 9. Positive Word

No	Positive Word	Amount
1	*Konservasi*	156
2	*Selamatkan*	89
3	*Adil*	31

Table 10. Negative Word

No	Negative Word	Amount
1	*Merusak*	195
2	*Hentikan*	138
3	*Bahaya*	85

Table 11. Neutral Word

No	Neutral Word	Amount
1	*Raja*	2426
2	*Lagi*	1696
3	*Sementara*	1091

b. Confusion Matrix

A confusion matrix is an evaluation table that shows the comparison between a model's predicted results and the actual data. This table contains the values of True Positive, True Negative, False Positive, and False Negative, which help indicate how many correct and incorrect predictions are made by the model. Based on the confusion matrix, performance metrics such as accuracy, precision, recall, and F1-score can be calculated, making it easier to clearly assess the performance of a classification model [22].

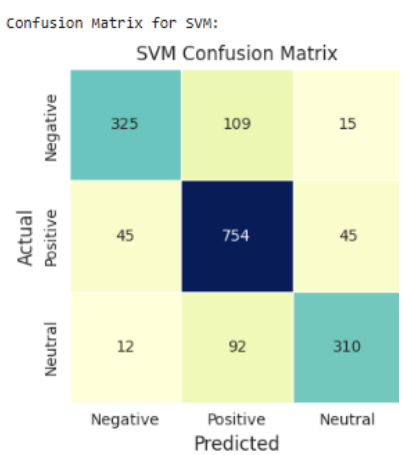

Figure 7. Confusion Matrix SVM

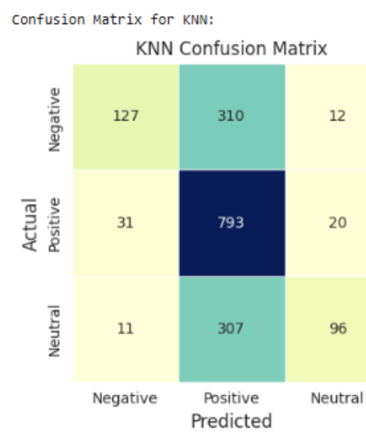

Figure 8. Confusion Matrix KNN

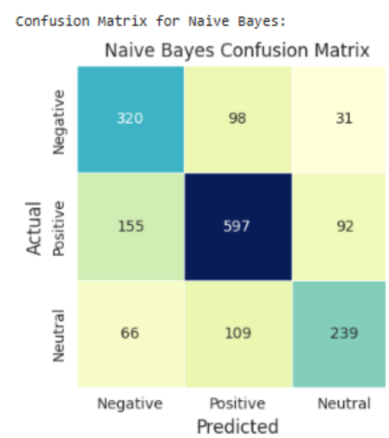

Figure 9. Confusion Matrix Naïve Bayes

The following is a table of confusion matrix for comparison of each algorithm can be seen below.

Table 12 Comparison of Correct Prediction (Diagonal Matrix)

Algorithm	Negative (True)	Neutral (True)	Positive (True)	Total Correct Prediction
SVM	325	754	793	**1.872**
KNN	127	793	96	**1.016**
Naïve Bayes	320	597	239	**1.156**

Table 12 presents a comparison of the number of correct predictions (diagonal values of the confusion matrix) produced by three classification algorithms, namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naive Bayes, across three sentiment classes: negative, neutral, and positive. For the SVM algorithm, the number of correct predictions is 325 for the negative class, 754 for the neutral class, and 793 for the positive class, resulting in a total of 1,872 correct predictions. These results indicate that SVM demonstrates relatively balanced performance and performs best in recognizing positive and neutral sentiments. For the KNN algorithm, the number of correct predictions is 127 for the negative class, 793 for the neutral class, and 96 for the positive class, with a total of 1,016 correct predictions. KNN shows its strongest performance in the neutral class; however, its performance declines significantly in the negative and positive classes.

Meanwhile, Naive Bayes achieves 320 correct predictions for the negative class, 597 for the neutral class, and 239 for the positive class, resulting in a total of 1,156 correct predictions. This algorithm is fairly effective in detecting negative sentiment but is less optimal in identifying positive sentiment compared to SVM. Overall, the table indicates that SVM achieves the highest total number of correct predictions, followed by Naive Bayes, while KNN exhibits the lowest performance. In addition, the neutral sentiment class is the most consistently recognized by all three algorithms compared to the other sentiment classes.

c. Model Accuracy Graph

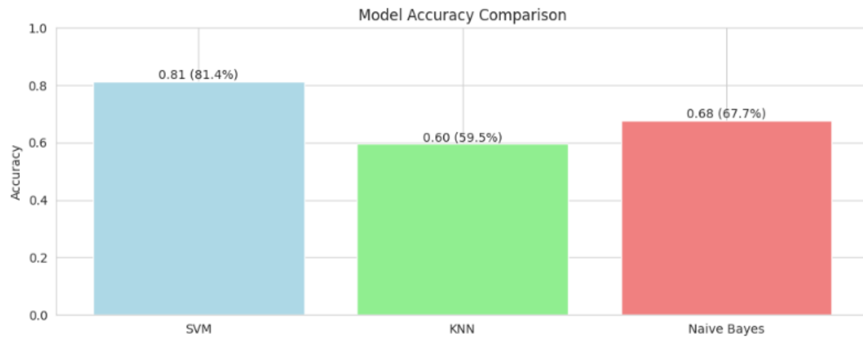

Figure 10. Model accuracy graph

The model accuracy graph shows a comparison of the performance of three classification algorithms, namely SVM, KNN, and Naive Bayes. SVM achieved the highest accuracy of 81.4%, making it the best-performing method in this study. Naive Bayes ranked second with an accuracy of 67.7%, while KNN had the lowest accuracy at 59.5%, indicating less optimal performance on the sentiment dataset [23].

d. Classification Report

Classification Report for SVM:

	precision	recall	f1-score	support
Negatif	0.851	0.724	0.782	449.000
Netral	0.790	0.893	0.838	844.000
Positif	0.838	0.749	0.791	414.000
accuracy	0.814	0.814	0.814	0.814
macro avg	0.826	0.789	0.804	1707.000
weighted avg	0.817	0.814	0.812	1707.000

Figure 11. Classification Report Of The SVM Algorithm

Classification Report for KNN:

	precision	recall	f1-score	support
Negatif	0.751	0.283	0.411	449.000
Netral	0.562	0.940	0.704	844.000
Positif	0.750	0.232	0.354	414.000
accuracy	0.595	0.595	0.595	0.595
macro avg	0.688	0.485	0.490	1707.000
weighted avg	0.658	0.595	0.542	1707.000

Figure 12. Classification Report Of The KNN Algorithm

Classification Report for Naive Bayes:

	precision	recall	f1-score	support
Negatif	0.591	0.713	0.646	449.000
Netral	0.743	0.707	0.725	844.000
Positif	0.660	0.577	0.616	414.000
accuracy	0.677	0.677	0.677	0.677
macro avg	0.665	0.666	0.662	1707.000
weighted avg	0.683	0.677	0.678	1707.000

Figure 13. Classification Report Of The Naïve Bayes Algorithm

Figure 11 to 13 show that SVM achieves the best and most balanced classification performance (accuracy 81%), followed by Naive Bayes with moderate performance (accuracy 68%), while KNN performs the worst, particularly in the negative and positive classes (accuracy 60%) [24].

Social Network Analysis

Social Network Analysis (SNA) is used to examine the relationships, proximity, and interaction patterns between actors in a social network [17]. In the Raja Ampat mining case study, SNA served to map network structures, identify influential supporting actors, and understand the distribution of opinions related to mining issues.

```
... SNA Quick Report:
- Number of nodes: 8
- Number of edges: 8
- Network density: 0.2857
- Top 3 betweenness centrality: [('A', 0.2619), ('C', 0.0952), ('E', 0.0476)]
- Closeness centrality for sample nodes: [('A', 0.5952), ('B', 0.4464), ('C', 0.5102), ('D', 0.3968), ('E', 0.4464)] ...
- Modularity: 0.28125
Partition (community per node):
  A: community 1
  B: community 1
  C: community 1
  D: community 2
  E: community 2
  F: community 1
  G: community 0
  H: community 0

DataFrame Summary for Reporting:
       metric     value
0   num_nodes  8.000000
1   num_edges  8.000000
2     density  0.285714
3  modularity  0.281250

Top 3 nodes by betweenness centrality:
  node  betweenness
0    A     0.261905
1    C     0.095238
2    E     0.047619
```

Figure 14. Network Centrality

The Social Network Analysis results show that the conversation network consists of 8 nodes and 8 edges, indicating a relatively small network with selective interactions among actors. The network density of 0.2857 suggests that only about 28% of all possible connections are present, meaning that interactions are not evenly distributed but concentrated on certain actors. The modularity value of 0.2813 indicates a moderately defined community structure, revealing the emergence of distinct interaction clusters, although the separation is not yet strong. Community detection identifies three main clusters, suggesting that actors tend to interact more frequently within their respective groups. This structure reflects a segmented communication pattern in the discourse surrounding nickel mining in Raja Ampat. Furthermore, several nodes exhibit higher betweenness centrality, particularly nodes A, C, and E, indicating their strategic role as bridges that facilitate information flow between communities. Overall, these findings suggest that public discourse on the issue is shaped by a limited number of key actors rather than being evenly distributed across the network. Influential actors were identified through four indicators: Degree Centrality, Closeness Centrality, Betweenness Centrality, and Eigenvector Centrality.

a. Degree Centrality

Degree centrality is the total number of direct connections an actor has [25]. It provides an initial indication of how popular or visible an actor is within a network. Actors with high degree have many connections and can often influence many individuals or groups. The results of the degree centrality measurement can be seen in **Table 13** below.

Table 13. Degree Centrality

Actor	Degree Centrality
@grok	0.043314
@recusant_raja	0.022708
@s	0.041632
@p	0.025652
@faktaberita89	0.042473
@elonmusk	0.019765
@rahulgandhi	0.009251

The Degree Centrality table presents the degree centrality values of each actor in the Twitter network. Degree centrality is a measure that indicates the number of direct connections an actor has with other actors in the network. The higher the degree centrality value, the more frequently the actor interacts with or is connected to others (for example, through mentions, replies, or retweets). Based on the table, the actor @grok has the highest degree centrality value (0.043314), followed by @fataberita89 (0.042473) and @s (0.041632), indicating that these three actors have more direct connections than other actors in the network.

b. Betweenness Centrality

Betweenness Centrality is used to identify nodes that act as connectors or bottlenecks in a network. This measure helps identify actors that play a crucial role in connecting one community to another [26]. The results of the Betweenness Centrality measurement can be seen in **Table 14** below.

Table 14. Betweenness Centrality

Actor	Betweenness Centrality
@grok	0.009782
@recusant_raja	0.006650
@s	0.004667
@p	0.004540
@faktaberita89	0.002119
@elonmusk	0.001283
@rahulgandhi	0.001228

Based on the **Table 14**, @grok has the highest betweenness centrality value (0.009782), followed by @recusant_raja (0.006650) and @s (0.004667). These three actors are considered the most influential because they frequently lie on the shortest communication paths between other actors, enabling them to serve as key connectors and to facilitate, accelerate, or influence the dissemination of information within the Twitter network.

c. Mention Count

Mention count is a measure of how often an account or node is mentioned by other accounts in a network. The higher the mention_count value, the greater the interaction or attention the account receives from other nodes in the network. The results of the mention_count measurement can be seen in **Table 15** below.

Table 15. Mention Count

Actor	Mention count
@grok	62
@recusant_raja	3
@s	29
@p	4
@faktaberita89	21
@elonmusk	24
@rahulgandhi	8

The Mention Count table shows the number of mentions received by each actor in Twitter conversations. Mention count reflects the level of attention and visibility of an actor within a discussion, where a higher number of mentions indicates that the actor is more frequently referenced and becomes a focal point of interaction. Based on the table, @grok has the highest mention count (62), followed by @s (29) and @elonmusk (24). These three actors are considered the most influential because they attract the greatest attention, are frequently referenced by other users, and play an important role in shaping the direction of discussions and the dissemination of information within the Twitter network.

d. Eigenvector Centrality

Eigenvector centrality is a measure used to determine the importance of a node in a network based on its connections, including the quality or influence of the nodes connected to it. A node with a high eigenvector centrality value indicates that the node has a significant contribution to the network structure [23]. In identifying key actors in a social network, eigenvector centrality is a key indicator for determining which nodes have the greatest influence. **Table 16** displays the results of the eigenvector centrality measurement.

Table 16. Eigenvector centrality

Actor	Eigenvector centrality
@grok	3.189196e-04
@recusant_raja	1.332914e-02
@s	3.116458e-02
@p	7.502983e-07
@faktaberita89	1.554457e-01
@elonmusk	6.774785e-04
@rahulgandhi	2.855804e-09

Based on the table, the actor @p has the highest eigenvector centrality value (0.7502983), followed by @grok (0.3189196) and @faktaberita89 (0.1554457). These three actors are considered the most influential because they have strong connections with other important actors in the network, placing them in strategically significant positions. Their relationships with influential actors enhance their role in strengthening information dissemination and shaping the overall network structure.

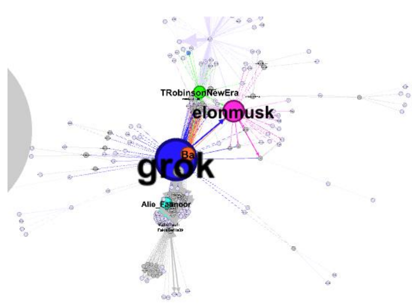

Figure 15. Gephi 0,10 visualization

Discussion

In terms of degree centrality, @recusant_raja has 103 direct connections, reflecting high popularity and broad engagement, followed by @grok with 99 connections, indicating similarly strong popularity. Meanwhile, @s has 54 direct connections, suggesting a less dominant role within the network.

The results show that public perceptions of mining in Raja Ampat are strongly influenced by concerns over environmental impacts, as reflected in the dominance of negative sentiment and the high activity of accounts criticizing the mining project [27]. In model evaluation, the three algorithms SVM, KNN, and Naive Bayes exhibited different performance characteristics. Naive Bayes remains a lightweight yet accurate method for public opinion analysis, particularly for Indonesian-language text with relatively simple structures [28]. SVM demonstrates high and consistent accuracy on well-preprocessed data but requires greater computational time and is sensitive to kernel parameter selection. Meanwhile, KNN shows the lowest performance among the three, as it is affected by the number of neighbors, distance measures, and inefficiency on large datasets [8].

Social Network Analysis (SNA) also reveals that actors with numerous connections and those serving as bridges between communities play a crucial role in disseminating narratives related to mining issues [29]. These findings are consistent with international studies indicating that sentiment analysis is effective for understanding public perceptions of social and environmental issues, while SNA is capable of identifying key actors within online communication networks [30]. Moreover, many studies confirm that Naive Bayes, SVM, and KNN are commonly used algorithms for opinion classification, although Naive Bayes and SVM generally outperform KNN in text-based domains [22].

This study has practical implications, such as helping governments understand public responses to mining issues, supporting environmental activists in identifying relevant actors for campaigns, and assisting policymakers in mapping the potential spread of misinformation based on network structures [31]. However, the study also has limitations, including reliance solely on Twitter data, which may not fully represent public opinion; algorithmic limitations such as Naive Bayes' limited ability to capture complex sentence context; and the possible presence of bot accounts. Therefore, future research is recommended to employ deep learning models such as BERT to improve accuracy, incorporate data from multiple platforms, conduct temporal analysis to observe sentiment dynamics over time, and apply bot detection techniques to enhance the reliability of network analysis [30].

4. Conclusion

This study demonstrates that sentiment classification combined with network-based actor identification can be applied in a reproducible and methodologically consistent manner to analyze public discourse on environmental conflict issues using social media data. Based on the final validated evaluation results, public sentiment toward the Raja Ampat mining conflict is predominantly neutral, while negative sentiment represents a substantial proportion of public concern, indicating critical responses within the discourse. The finalized Social Network Analysis confirms that influence within the communication network is concentrated among a limited number of structurally central actors. Degree and betweenness centrality measures consistently indicate that these actors play a key role in shaping information flow and facilitating the dissemination of narratives related to the mining issue.

From a methodological perspective, the comparative evaluation shows that Support Vector Machine and Naive Bayes models provide more stable and reliable performance than K-Nearest Neighbor under the reported experimental setup, as evidenced by confusion matrix–based metrics. All conclusions are strictly derived from the final validated classification results and the finalized network construction. Overall, this research contributes empirical evidence to sentiment analysis and actor identification in the context of environmental conflict discourse on social media. By emphasizing metric-based validation and transparent network construction, the proposed approach supports reproducibility and can serve as a reference framework for future data science studies in similar domains.

References:

[1] Y. Qi and Z. Shabrina, "Sentiment analysis using Twitter data: a comparative application of lexicon- and machine-learning-based approach," *Soc. Netw. Anal. Min. 2023 131*, vol. 13, no. 1, pp. 31-, Feb. 2023, doi: 10.1007/S13278-023-01030-X.

[2] B. Pang and L. Lee, "Opinion Mining and Sentiment Analysis," *Found. Trends® Inf. Retr.*, vol. 2, no. 1–2, pp. 1–135, 2008, doi: 10.1561/1500000011.

[3] L. C. Freeman, "Centrality in social networks conceptual clarification," *Soc. Networks*, vol. 1, no. 3, pp. 215–239, 1978, doi: 10.1016/0378-8733(78)90021-7.

[4] A. Sharma and S. Dey, "A comparative study of selection and machine learning techniques for sentiment analysis," *Proceeding 2012 ACM Res. Appl. Comput. Symp. RACS 2012*, pp. 1–7, 2012, doi: 10.1145/2401603.2401605.

[5] B. Saberi and S. Saad, "Sentiment analysis or opinion mining: A review," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 7, no. 5, pp. 1660–1666, 2017, doi: 10.18517/ijaseit.7.5.2137.

[6] S. Peng, G. Wang, and D. Xie, "Social Influence Analysis in Social Networking Big Data: Opportunities and Challenges," *IEEE Netw.*, vol. 31, no. 1, pp. 11–17, Jan. 2017, doi: 10.1109/MNET.2016.1500104NM.

[7] N. Parveen, P. Chakrabarti, B. T. Hung, and A. Shaik, "Twitter sentiment analysis using hybrid gated attention recurrent network," *J. Big Data 2023 101*, vol. 10, no. 1, pp. 50-, Apr. 2023, doi: 10.1186/S40537-023-00726-3.

[8] N. Öztürk and S. Ayvaz, "Sentiment analysis on Twitter: A text mining approach to the Syrian refugee crisis," *Telemat. Informatics*, vol. 35, no. 1, pp. 136–147, Apr. 2018, doi: 10.1016/J.TELE.2017.10.006.

[9] B. Dahal, S. A. P. Kumar, and Z. Li, "Topic modeling and sentiment analysis of global climate change tweets," *Soc. Netw. Anal. Min.*, vol. 9, no. 1, pp. 1–20, 2019, doi: 10.1007/s13278-019-0568-8.

[10] S. F. Fattah and Purnawansyah, "Analisis sentimen terhadap Body Shaming pada Twitter menggunakan Metode Naïve Bayes Classifier," *Indones. J. Data Sci.*, vol. 3, no. 2, pp. 61–71, 2022, doi: 10.56705/ijodas.v3i2.46.

[11] B. K. Bhavitha, A. P. Rodrigues, and N. N. Chiplunkar, "Comparative study of machine learning techniques in sentimental analysis," *Proc. Int. Conf. Inven. Commun. Comput. Technol. ICICCT 2017*, no. Icicct, pp. 216–221, 2017, doi: 10.1109/ICICCT.2017.7975191.

[12] A. Wahbeh, T. Nasralah, M. Al-Ramahi, and O. El-Gayar, "Mining Physicians' Opinions on Social Media to Obtain Insights Into COVID-19: Mixed Methods Analysis.," *JMIR public Heal. Surveill.*, vol. 6, no. 2, p. e19276, Jun. 2020, doi: 10.2196/19276.

[13] J. Hartmann, J. Huppertz, C. Schamp, and M. Heitmann, "Comparing automated text classification methods," *Int. J. Res. Mark.*, vol. 36, no. 1, pp. 20–38, Mar. 2019, doi: 10.1016/J.IJRESMAR.2018.09.009.

[14] J. D. M. Rennie, L. Shih, J. Teevan, and D. R. Karger, "Tackling the Poor Assumptions of Naive Bayes Text Classifiers," no. 1973, 2003.

[15] E. Cambria, B. Schuller, Y. Xia, and C. Havasi, "New avenues in opinion mining and sentiment analysis," 2013.

[16] G. Wang, J. Sun, J. Ma, K. Xu, and J. Gu, "Sentiment classification: The contribution of ensemble learning," *Decis. Support Syst.*, vol. 57, no. 1, pp. 77–93, Jan. 2014, doi: 10.1016/J.DSS.2013.08.002.

[17] U. Aditiawarman, M. Lumbia, T. Mantoro, and A. A. Ibrahim, "Social Network Analysis: Identification of Communication and Information Dissemination (Case Study of Holywings)," *J. Online Inform.*, vol. 8, no. 1, pp. 19–26, 2023, doi: 10.15575/join.v8i1.911.

[18] U. D. Gandhi, P. Malarvizhi Kumar, G. Chandra Babu, and G. Karthick, "Sentiment Analysis on Twitter Data by Using Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM)," *Wirel. Pers. Commun. 2021*, pp. 1–10, May 2021, doi: 10.1007/S11277-021-08580-3.

[19] M. Rodríguez-Ibánez, A. Casánez-Ventura, F. Castejón-Mateos, and P. M. Cuenca-Jiménez, “A review on sentiment analysis from social media platforms,” *Expert Syst. Appl.*, vol. 223, p. 119862, Aug. 2023, doi: 10.1016/J.ESWA.2023.119862.

[20] A. R. Sembiring and C. K. Dewa, “Sentiment Analysis On Indonesian Tweets about the 2024 Election,” *Sinkron*, vol. 9, no. 1, pp. 413–422, 2025, doi: 10.33395/sinkron.v9i1.14481.

[21] A. Giachanou, “Like It or Not : A Survey of Twi er Sentiment Analysis Methods Open Access Support provided by : Like It or Not : A Survey of Twitter Sentiment Analysis Methods,” vol. 49, no. 2, 2026, doi: 10.1145/2938640.

[22] J. Samuel, G. G. M. N. Ali, M. M. Rahman, E. Esawi, and Y. Samuel, “COVID-19 Public Sentiment Insights and Machine Learning for Tweets Classification,” *Inf. 2020, Vol. 11, Page 314*, vol. 11, no. 6, p. 314, Jun. 2020, doi: 10.3390/INFO11060314.

[23] S. P. Borgatti, “Centrality and network flow,” *Soc. Networks*, vol. 27, pp. 55–71, 2005, doi: 10.1016/j.socnet.2004.11.008.

[24] D. Chicco and G. Jurman, “The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation,” pp. 1–13, 2020.

[25] U. Brandes, “A faster algorithm for betweenness centrality,” *J. Math. Sociol.*, vol. 25, no. 2, pp. 163–177, 2001, doi: 10.1080/0022250X.2001.9990249;WEBSITE:WEBSITE:TFOPB;PAGEGROUP:STRING:PUBLICATION.

[26] U. Brandes, “On Variants of Shortest-Path Betweenness Centrality and their Generic Computation 1,” vol. 30, no. November 2007, pp. 136–145, 2008.

[27] I. Technology, F. S. Nufus, W. Gata, C. Science, and U. N. Mandiri, “Sentiment Analysis of Public Opinion on Transportation,” vol. 22, no. 2, pp. 426–432, 2025.

[28] E. Zarrabeitia-Bilbao, M. Jaca-Madariaga, R. M. Rio-Belver, and I. Álvarez-Meaza, “Nuclear energy: Twitter data mining for social listening analysis,” *Soc. Netw. Anal. Min.*, vol. 13, no. 1, pp. 1–17, 2023, doi: 10.1007/s13278-023-01033-8.

[29] A. Khan *et al.*, “Predicting Politician’s Supporters’ Network on Twitter Using Social Network Analysis and Semantic Analysis,” *Sci. Program.*, vol. 2020, 2020, doi: 10.1155/2020/9353120.

[30] J. Jagdale, R. Sreemathy, B. Jagdale, and K. Ghag, “Mapreduce framework based sentiment analysis of twitter data using hierarchical attention network with chronological leader algorithm,” *Soc. Netw. Anal. Min. 2024 141*, vol. 14, no. 1, pp. 172-, Aug. 2024, doi: 10.1007/S13278-024-01293-Y.

[31] A. P. Logan, P. M. LaCasse, and B. J. Lunday, “Social network analysis of Twitter interactions: a directed multilayer network approach,” *Soc. Netw. Anal. Min. 2023 131*, vol. 13, no. 1, pp. 65-, Apr. 2023, doi: 10.1007/S13278-023-01063-2.