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Sentimental Analysis of Twitter Data Using Machine Learning and Deep Learning: Nickel Ore Export Restrictions to Europe Under Jokowi's Administration 2022

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A B S T R A C T

Nowadays, social media has evolved into a powerful networked ecosystem in which governments and citizens publicly debate economic and political issues. This holds true for the pros and cons of Indonesia's ore nickel export restriction to Europe, which we aim to investigate further in this paper. Using Twitter as a dependable channel for conducting sentiment analysis, we have gathered 7070 tweets data for further processing using two sentiment analysis approaches, namely Support Vector Machine (SVM) and Long Short Term Memory (LSTM). Model construction stage has shown that Bidirectional LSTM performed better than LSTM and SVM kernels, with accuracy of 91%. The LSTM comes second and The SVM Radial Basis Function comes third in terms of best model, with 88% and 83% accuracies, respectively. In terms of sentiments, most Indonesians believe that the nickel ore provision will have a positive impact on the mining industry in Indonesia. However, a small number of Indonesian citizens contradict this policy due to fears of a trade dispute that could potentially harm Indonesia's bilateral relations with the EU. Hence, this study contributes to the advancement of measuring public opinions through big data tools by identifying Bidirectional LSTM as the optimal model for the dataset.

Keywords: Sentiment Analysis, Nickel Ore Export, Twitter, Machine Learning, Deep Learning

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Ⅰ. Introduction

Nickel is a vital commodity in the global commerce arena. Over 300.000 goods contain nickel in the form of over 3.000 alloys. It is a high-end material that is utilized in construction, vehicles, petrochemicals, fabrication and welding, renewable energy, electronics, transportation, and water. The stainless steel sector is the largest consumer of primary and scrap nickel, followed by alloys, special steel, plating, batteries, and foundries. Due to its wide range of uses, nickel is in high demand by various countries in the world. Since 2010, global primary nickel consumption has increased at a rapid pace, surpassing 2 million tons in 2016. Even more, the COVID-19 pandemic did not appear to have a substantial influence on global primary nickel consumption in 2020 (International Nickel Study Group, 2021). Given the enormous and ever-increasing demand for nickel on the global market, nickel exports should be a top priority for the countries with the greatest quantity of nickel reserves, including Indonesia.

According to Mineral Commodity Summaries 2022, Indonesia is the world's largest nickel-producing country, followed by the Phillipines, Russia, and New Caledonia (U.S. Geological Survey, 2022). However, despite Indonesia's position as the world's leader in nickel-producing country, the contribution of nickel sales to Indonesia's economic growth is neither as important nor significant. In contrast to the aforementioned Indonesian nickel potential, it is coal that accounted for around 85% of state revenue from the mining sector (International Labour Organization, 2022). The reason for the insignificance of revenue from nickel products is that Indonesia only exports the ore of existing nickel, which has a relatively low selling price. With nickel's enormous potential in Indonesia, it would be unfortunate if this mining commodity was not adequately developed and utilized. Therefore, to encourage Indonesia's domestic economic growth, a series of policy on nickel ore export restriction was implemented.

In the pursuit of economic growth and industrial development, nations often implement strategic plans aimed at maximizing the use of their natural resources. Indonesia made a similar move during President Joko Widodo's tenure by establishing restrictions on the export of nickel ore. This approach aimed to preserve local nickel demand and generate additional value and economic resilience by optimizing downstream operations. By going downstream, the government hopes that industrial entities will process coal and nickel ore into finished or partially completed products instead of exporting them in raw form. It is also expected that the policy restricting exports will ultimately increase the export prices of Indonesian nickel, resulting in positive growth for Indonesia's Gross Domestic Product (GDP).

However, the policy of prohibition on nickel ore exports from Indonesia has been a source of contention since Joko Widodo's election in July 2014. This strategy played a pivotal role in reshaping the global nickel market, especially in Europe, a significant consumer of nickel products. The European Union (EU) has expressed major disapproval to the export embargo policy, which has been in effect since 2020. According to its government, the EU feels disadvantaged because its nickel-based processing industry may be disrupted, and Indonesia's policies are deemed to have violated a number of provisions in the General Agreement on Tariffs and Trade (GATT). Perceiving robust legal foundations and safeguards, the EU brought legal action against Indonesia at the World Trade Organization (WTO), marking the start of a trade dispute between Indonesia and the European Union.

The ongoing trade dispute lawsuit has also sparked heated debate among Indonesians. Some Indonesians argue that the current export restriction on nickel ore is the appropriate course of action, signaling national support for economic sovereignty and industrial growth. Yet, others contend that the restriction of nickel ore exports is not the best approach that the government can implement. This pessimistic view underscore concerns about global supply chain disruptions and economic repercussions. This contentious argument continues to expand on social media, resulting in polarization that separates society into combative factions with opposing views on the prohibition of nickel ore exports.

Additionally, this debate also shows that social media has enable internet users to participate in political debates and promote their opinions and interests in real time (Graham et al., 2014). It also has the ability to connect decision-makers to audiences in real time, which is now known as e-diplomacy or digital diplomacy. The ensuing substance of public opinions could help to shed light on the social and discursive processes of a particular political or economic issue. Social media content can also reveal a variety of societal political inclinations and potentially proclaim for different policy and decision-making pathways (Blazquez and Domenech, 2018; Hürlimann et al., 2016). Given the strategic importance of information in defining decision-making processes and determining decision-quality, decision-makers must be able to glean insights from fast changing public responses to policies and activities (Elgendy and Elragal, 2016). As a result, governments are seeking information to understand the perspectives and preferences of citizens regarding the likely outcomes of many government-related issues in the political, economic, and other arenas. Regarding Indonesia's policy of prohibiting the export of nickel ore to the European Union, analyzing social discourse can be a valuable tool for the government in formulating future plans and strategies in carrying out this contentious policy.

In this research, we uses sentiment analysis (SA) approach to the study of tweets concerning nickel ore export prohibiton. SA is an opinion mining technique that analyzes opinion-oriented textual data to discover its user polarity in the form of emotions, perceptions, and sentiments (Georgiadou et al., 2020). Known as the widely used instrument in public opinion extraction, sentiment analysis supports decision making by identifying positive or negative opinions towards policy and product. With the earlier-mentioned method of SA, we apply SA of tweets to decipher citizens' preferences expressed through their sentiment (positive or negative) towards nickel ore export prohibition policy that was communicated on Twitter for the period of this research. We placed our focus on post-pandemic policy implementation, during an intense phase of local economic resilience and post-pandemic recovery throughout 2022. Our finding allow us to examine whether Indonesians favours certain prospective negotiating outcomes over others, and hence potentially provide a digital signal of citizens' sentiment toward the prohibition of nickel ore exports.

Prior research on Indonesian nickel ore export ban has mainly addressed the prospect of value-added nickel development in Indonesia (e.g., Soelistijo, 2013), legal aspect of the policy (e.g., Widiatedja, 2021), its impact on the Indonesians and local mining industry (e.g., Ardianti and Lestari, 2023; Kurniawan et al., 2021; Pandyaswargo et al., 2021), the lawsuit that occurred (e.g., Krustiyati and Christine, 2022), and the policy's effect on global market (e.g., Lim et al., 2021; Ma et al., 2022). As for the study on public opinions in regard to a valuable asset for decision-making is scarce. Therefore, this study aims to cover the research gap on nickel ore export ban with a different approach to the issue by developing an architecture for analyzing the sentiment of the Indonesians through machine learning and deep learning. The findings will subsequently be transformed into policy recommendations for the government and stakeholders to determine next policy implementation steps. In doing so, this study contributes to both the domains of sentiment analysis and international relations (IR). It sheds light on the sentiment dynamics around an important economic policy decision and serves as a case study for the efficiency of sentiment analysis tools in comprehending complex geopolitical situations.

Ⅱ. Conceptual Background

2.1. Twitter and Data Mining in Government Policy

With social media becoming increasingly prevalent in decision-making as an alternate way of collecting user information, organizations and decision-makers who aim to make informed decisions are looking for solutions to extract intelligence and gain insights from large volumes of rapidly changing data (Aladwani and Dwivedi, 2018; Elgendy and Elragal, 2016). This is advantageous for policymakers who require information to decide how an organization or government should act on a new issue, especially a controversial one (Grubmüller et al., 2013). For example, in the run-up to the Iran-P5+1 nuclear talks in 2015, Twitter indicated both public opinion and the Iranian regime's preference for a positive outcome, an intention that was critical to the successful implementation of the Joint Comprehensive Plan of Action (JCPOA) (Duncombe, 2017).

Public opinion extraction can be conducted using various social media sites, including Twitter. Moreover, Twitter has evolved into an influential networked environment in which individuals, including ordinary citizens and government leaders, publicly debate economic and political issues (Duncombe, 2019; Guerrero-Solé, 2018). In fact, the users of Twitter continue to increased rapidly, at least until 2022.[1] A rising number of studies have explored the relationship between Twitter and politics, claiming that Twitter users desire to open the political realm to new ideas (Hall et al., 2018). As a result, these studies proposed that digital interactions between the government and internet citizens (netizens) on Twitter could serve as a channel for capturing public sentiment swings and factoring those public sentiments into decision-making, allowing organizations to make informed decisions that are acceptable to citizens. Consequently, Twitter can be a useful instrument for policymakers to obtain real-time information regarding public preferences in relation to their policies and decisions. Research procedures have recently seen a substantial advancement with the analysis of such datasets (Grčar et al., 2017).

Recent works on Twitter and data mining for government policy has shown significantly improved results every year. In COVID-19 case, sentiment analysis and topic modeling provide valuable insights into the discussion of the COVID-19 pandemic on social media, as well as alternative perspectives to investigate the crisis. This has shown that Twitter is an effective communication channel for under-

1) https://www.statista.com/statistics/303681/twitter-users-worldwide/

standing public concern and awareness about COVID-19 that provide easy access for health departments in addressing public concerns about the disease (Boon-Itt and Skunkan, 2020; Naseem et al., 2021). Not only from a health perspective, some uses of Twitter as material for formulating government policies are also applied in the business and economic sectors (Altig et al., 2020; Carracedo et al., 2021; Prentice et al., 2020). Apart from that, Twitter and data mining is also widely used in making policies in the political field, such as election campaigns and voters prediction (Grover et al., 2019). This shows that Twitter is a valuable field in policy formulation and public opinion is a valuable asset for the government.

2.2. Sentiment Analysis With Machine Learning and Deep Learning

In the area of scientific research, sentiment analysis is one of the hottest study subjects (Medhat et al., 2014). Several studies have postulated that sentiment analysis is the computational study of people's opinions, assessments, behaviors, and emotional reactions regarding other individuals, things, issues, events, and subjects (Liu, 2012). As a branch of Natural Language Processing (NLP), sentiment analysis entails gathering opinions in textual form and classifying them computationally based on their polarity, such as whether they are positive, negative, or neutral.

During the last decade, an immense quantity of internet-based information has been pitched in, including blog entries, posts, and comments on social media. These kinds of data can be utilized adequately to gather useful information by employing sentiment analysis techniques, such as lexicon-based, machine learning, and deep learning. Based on a study conducted by Wankhade et al. (2022), supervised machine learning algorithms are frequently the most prevalent approach in this field because of their ease of use and high accuracy, wherein classification using the Naïve Bayes (NB) and Support Vector Machine (SVM) algorithms is widely used as a benchmark to evaluate newly developed methods. In their systematic literature studies on SVM, Ahmad et al. (2018) identifies that sentiment analysis researchers commonly used SVM with other techniques applicable to produce and compare which techniques produce the most satisfying accuracy. In 2019, Rahat et al. used SVM and Naïve Bayes to classify airline reviews that produced satisfactory outcomes when SVM was utilized as a polarity classifier. It is also highlighted that the accuracy comparison value revealed that the SVM performed better than the Naïve Bayes algorithm (Rahat et al., 2019). Other researchers supported the outcome stating that SVM had a good performance to classify opinions than other supervised machine learning techniques such as Naïve Bayes (Naing et al., 2019; Pratama et al., 2019) and Random Forest (Leelawat et al., 2022). SVM also rarely produces an accuracy value lower than 90% (Chory et al., 2019; Naw and Mon, 2018). This is consistent with the result obtained by Devika et al. (2016) who lists three advantages that SVM has to offer: sparse document vector, few irrelevant features, and the ability to transform and deal with high dimensional input spaces.

To gain the most accurate result, SVM was further optimized for several sentiment analysis research using Fisher Kernel (Han et al., 2020), Normalized Poly Kernel (Prastyo et al., 2020), and other four kernels of SVM, which are Linear, Radial Basis Function (RBF), Polynomial, and Sigmoid to map non linearly separable dataset into a higher dimension. This makes it simple for SVM to transform the data into linear in order to speed up the classification process (Mourya et al., 2020; Rahardi et al., 2022; Vijay and Verma, 2022). Therefore, it is important to try out different kernels in SVM to achieve the best accuracy result. This study will implement the four kernels of SVM that is further optimized using appropriate parameters and iterated thoroughly with GridSearchCV.

However, the supervised learning technique like SVM had limitations because it applies the method of training and testing which generally takes a long time to obtain the result (Razali et al., 2021). But at the same time, supervised machine learning works better than the unsupervised one in a small, structured dataset with few variables predictor (Nguyen et al., 2022). This contradictory opinion serves as an interesting start for research. Besides, analyzing the selected articles revealed that the accuracy of findings may be affected by the following factors: the procedures and techniques of the preprocessing phase, the selection of input dataset together with its subject, and the ratio of training data to test data (in the case of a supervised classifier). As a result, this study seeks to obtain a different perspective in order to classify opinions using another appropriate technique that is known to have a relatively short training time, which is generally recognized as deep learning technique.

Deep learning, which uses deep neural networks, is a subfield of machine learning. In deep learning, multilayer neural networks can perform both linear and nonlinear transformations to extract the features of the data and enable the computer to observe, identify, and respond to complicated situations (Day and Teng, 2017). Common deep learning methods that are widely used are convolutional neural networks (CNN) and Recurrent Neural Networks (RNN). Although most deep learning models have shown to be effective, a number of issues still need to be addressed, such as exploding and vanishing gradients, challenges with model interpretation, related parameter settings, complex model training, and how to maintain a specific accuracy rate while accelerating training speed (Chen et al., 2020; Day and Teng, 2017; Tai et al., 2015). To overcome the aforementioned problems, Hochreiter and Schmidhuber introduced LSTM (Long Short Term Memory) as an improved RNN with a memory cell that can maintain its state for an extended period of time (Tai et al., 2015). LSTM consists of three parts: input layer, output layer and forgot gate. In order to address the issues with inadequate long-term learning of recurrent neural networks, LSTM utilizes a forgot gate to select the data that must be memorized or forgotten (Day and Lin, 2017).

In this study, LSTM is used to examine public opinion on the nickel export ban, but we also employ Bidirectional LSTM to compare model accuracy. As noted by Chen et al. (2020), Bidirectional Long Short Term Memory (Bi-LSTM) was first applied by Graves to increase the performance of the conventional LSTM model by extracting more precise features. To retrieve the forward and reverse context messages, this architecture employs two LSTMs running in opposite directions, namely an LSTM forward layer and an LSTM backward layer, which run from the beginning and conclusion of the sequence, respectively. Each output is the result of merging the outputs of the forward layer and the backward layer from two LSTMs. Known for its capability of maintaining cell memory that sets it apart from feed-forward networks, LSTM and Bi-LSTM have been applied in several sentiment analysis research in public health sector (Imran et al., 2020), linguistics (Pasupa and Seneewong Na Ayutthaya, 2019), financial and business-related issues (Day and Teng, 2017).

LSTM not only has a high-capacity memory, but also known to be effective for tasks involving NLP and beneficial for tasks that require understanding context. Meanshile, SVMs are also known to be effective in high-dimensional feature spaces, making them suitable for tasks with a large number of features. Additionally, SVMs are less prone to overfitting, especially in high-dimensional spaces, due to the margin maximization objective. This makes them useful when dealing with datasets with a small number of samples. Least, SVMs also offer versatility in kernel functions. With linear, polynomial, sigmoid, and radial basis functions, SVMs can also build for multi-classification problems by mapping data into higher-dimensional spaces. This flexibility enables SVMs to handle non-linear relationships in the data. These algorithms from ML and DL are each known for their best performance towards textual dataset.

Various studies have used SVMs and LSTMs separately, as they represent different learning methods. Their accuracy may appear superior individually, but what if SVM and LSTM are used together with the same dataset? Will LSTM outperform SVM because it is part of unsupervised learning, or vice versa? To answer these questions, this research aims to gather public sentiment towards nickel export restrictions using machine learning and deep learning to provide valuable insights for the government, academics, and interested civilians. To enhance the accuracy performance of SVM, we will also utilize available kernels to test if SVM with kernels will come out to be the most optimal model for textual datasets, particularly Twitter datasets.

Ⅲ. Research Methodology

3.1. Dataset

This research uses Indonesian society's tweets regarding nickel export restriction from twitter as a dataset, ranging from 1 January 2022 to 31 December 2022. Using keywords 'indonesian nickel export restriction' and several related issues around it, we have successfully crawled 7070 tweets through Twitter Application Programming Interface (API) developer tools with a scraping script by utilizing Tweepy library, which organizes our tweet data into a topic-based dataset using the provided keyword and a tweet scrape date number. This consist of a keyword, a maximum number of tweets per subject, tweet date ranges, and primary tweet language. To perform dataset cleaning, we use regular expression, casefold, lemmatization, stopword removal, stem, and tokenize to make sure that the dataset is free of any writing errors. After cleaning dataset, we duplicate our dataset for two different purposes, the first one for analyzing sentiments independently, and the second one for experimenting with the models. For ML or DL models, the cleaned dataset was divided into train data and test data with a percentage ratio of 80:20.

After compiling and cleaning the dataset itself, we label the dataset into three categories: positive, negative, and neutral. This step was executed by TextBlob, a tool designed exclusively for data preprocessing in the sentiment analysis process. TextBlob is a Python library that offers a simple API for common natural language processing (NLP) tasks, such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, and translation. It is built on top of NLTK (Natural Language Toolkit) and provides a user-friendly interface for basic NLP operations without requiring knowledge of lower-level implementations. TextBlob offers a simple and user-friendly API and the library simplifies many complexities, enabling users to perform common tasks with minimal code.

Additionally, TextBlob includes a pre-trained sentiment analysis model that can classify text as positive, negative, or neutral. This feature can be useful for tasks such as sentiment labelling. TextBlob also ensures more accurate and precise results in sentiment analysis cases, outperforming Afinn and VADER (Valence Aware Dictionary for Sentiment Reasoning) (Aljedaani et al., 2022). In this research, we utilized two methods for data labeling. First, we automatically labeled the data using TextBlob for all the tweets we collected. The purpose of this is to determine the true public sentiment that occurs in public discourse. After completing the initial labeling, we duplicated the same dataset and only labeled the training data for the purpose of building ML and DL models.

Next, to deepen our analysis of the tweet data, we also performed topic modeling using Latent Dirichlet Allocation (LDA). LDA is an automated method for identifying topics within a collection of text documents. It is especially useful when dealing with large amounts of unstructured text data and seeking to comprehend the underlying themes or subjects. LDA is also an unsupervised learning algorithm, which means it does not require labeled training data. This makes it applicable in situations where predefined categories or topics may not exist.

In addition, LDA identifies topics and provides information about their distribution within individual documents, allowing for a better understanding of document structure in terms of underlying topics better than Latent Semantic Analysis (LSA) performance (Mohammed and Al-Augby, 2020). Although LDA has many advantages, it also has limitations. For example, it assumes that documents are mixtures of topics and that words are assigned to topics based on a probabilistic process. Additionally, it may not perform well on very short documents, and the number of topics must be specified in advance. Despite these limitations, LDA remains a powerful tool for exploring and understanding large textual dataset.

3.2. Model Construction

After the labelling step for train data has been completed, we try to build the sentiment classification model. It is widely accepted that both machine learning and deep learning classifier are incapable of handling textual (string) dataset (Lyu and Takikawa, 2022), therefore it must be transformed into vectors. In this work, we use Term Frequency – Inverse Document Frequency (TF-IDF) vectorization as the feature extraction tool. The TF-IDF method can be loosely stated as a method for weighing the relationship of a word (term) to a document. In this method, the weights are determined by combining the inverse document frequency and word frequency. Calculating the frequency of a word appearing in a document is a procedure known as term frequency. The phrases that appear in different documents are calculated using the inverse document frequency method, which reduces their significance to the document by treating them as general terms (Chory et al., 2019). Outperforming N-Gram features, BM25, and Word2Vec, TF-IDF is acknowledged as the most accurate feature extraction method ever utilized for ML models (Ahuja et al., 2019; Cahyani and Patasik, 2021; Kadhim, 2019).

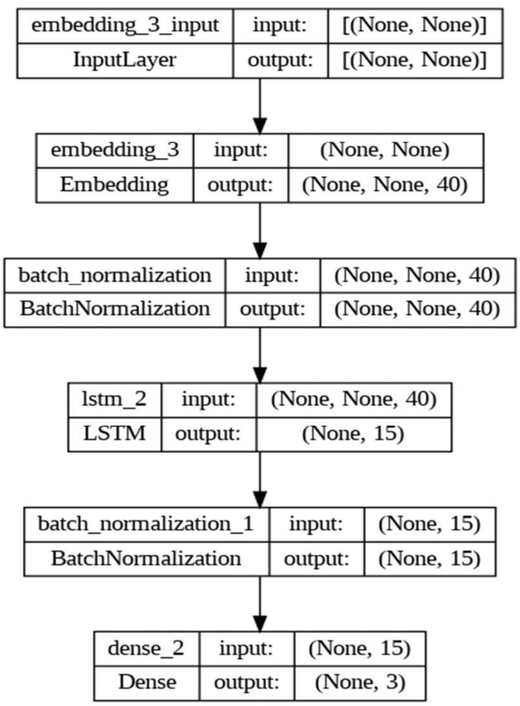
In this paper, we use SVM, a subset of machine learning, to classify the tweets. Classification is performed by studying the boundary line (decision boundary) that divides one class from another using support vector and margin scores, in which case the line helps to distinguish between positive and negative tweets (Neogi et al., 2021; Sontayasara et al., 2021).

<Table 1> Kernels of SVM

Kernels	Functions	
Linear	$K(x_i, x_j) = x^T. X_j$	(1)
Radial basis function	$K(x_i, x_j) = \exp(- \| x - x_j \| 2/2\ ^{2})$	(2)
Polynomial	$K(x_i, x_j) = (x^T. x_j + 1)^d$	(3)
Sigmoid	$K(x_i, x_j) = \tanh(\alpha < x_i . x_j > + \beta)$	(4)

To increase the accuracy value of our model, we also implement kernels of SVM which appears to be a huge benefit for unstructured non-linear dataset. Types of kernels in SVM that can be used are presented in <Table 1> below.

In this research, we also use RNN-LSTM as a deep learning technique to classify tweets. RNN is a neural network that purposefully run several times, with bits of each run will feed the next one. RNNs are especially helpful for evaluating sequences because the layers can pick up information from how the neural network performed on earlier portions of the sequence in previous runs (Nemes and Kiss, 2021). To gain different perspectives in model building, we applied LSTM and Bi-LSTM. Each techniques will be implemented solely in each model, producing different accuracies that will be useful for model comparison.

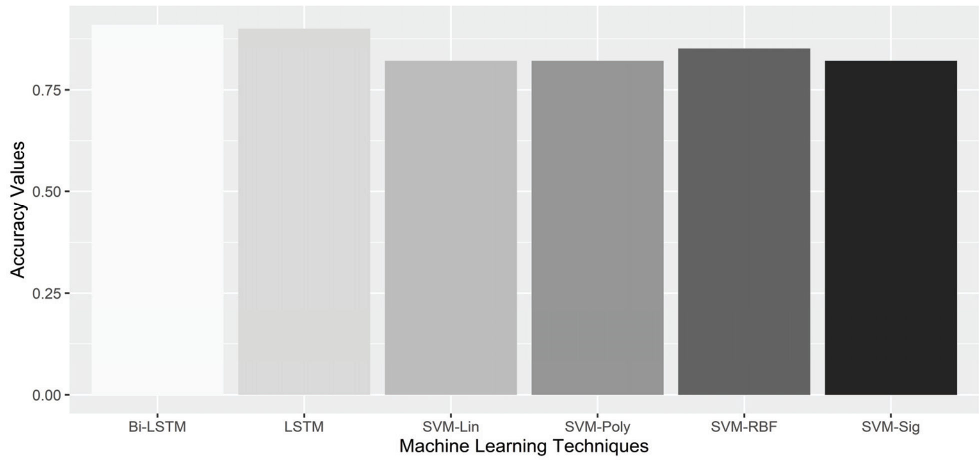


<Figure 1> The Architecture of RNN-LSTM Sequential Deep Learning Layers

The model was created using Tensorflow and Keras tools. Using Python version 3.10.6, we created a sequential model by passing a list of layer instances to the constructor with the first layer being the embedding layer. With random weights as its initialization, the embedding layer will eventually learn each word in the training dataset. After that, to prevent overfitting, we implement batch normalization layers, as these layers are known to be robust towards overfitting. Subsequent to the normalization layers, we applied LSTM and Bi-LSTM as the wrappers on these layers. The Dense and Dropout layers come next. Each input node is coupled to each output node in a dense layer, which is a traditional fully connected neural network layer as can be seen in <Figure 1>.

Ⅳ. Results Analysis

Turning now to the experimental evidence on sentimental analysis of Indonesian nickel export restriction, fresh mined dataset has been analyzed fur-

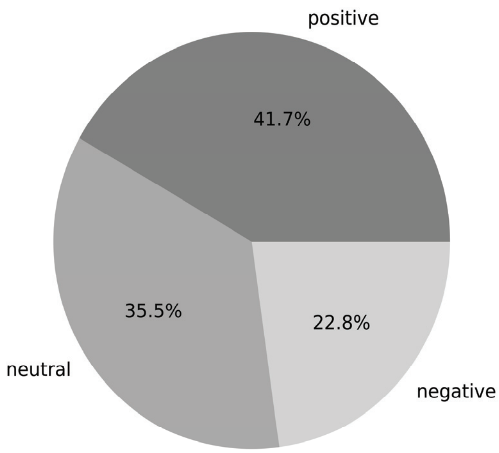


<Figure 2> Comparison of Several Machine Learning Techniques That Were Applied

ther using machine learning and deep learning techniques. Model comparisons were carried out using Python 3.7.0 and have been visualized through third party applications. The results obtained from model construction stage using SVM and its four kernels which is followed by deep learning techniques of LSTM and Bidirectional LSTM can be compared in <Figure 2> below.

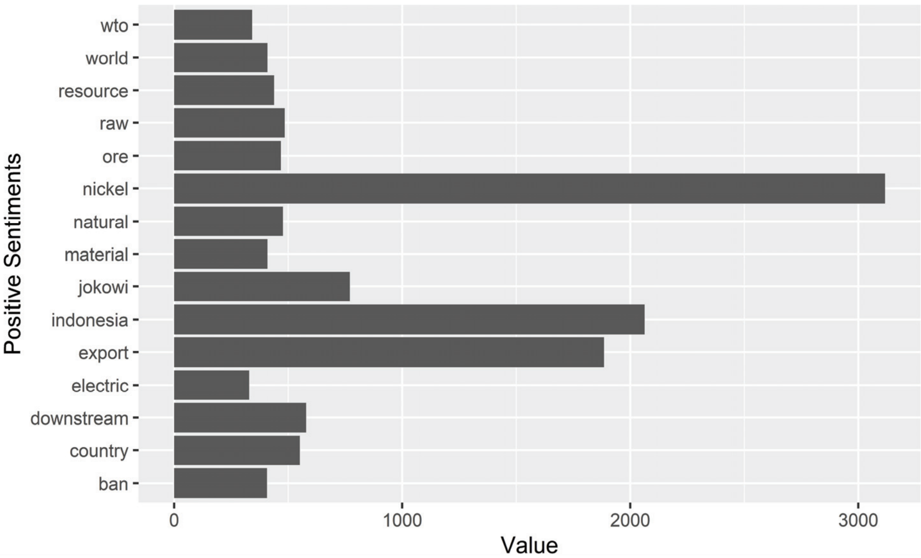
It is apparent from <Figure 2> that Bidirectional LSTM reached the highest accuracy compared to other machine learning techniques applied, where it performed well to achieve its peak at 91%. LSTM also occupies the second position as the model that produces the highest accuracy, which is 88%. This demonstrates that deep learning can still perform well on relatively limited datasets as long as the model is built with the right approaches and layers. This finding is contrary to previous studies which have suggested that in a small dataset with a few structured variables, machine learning will outperform deep learning in terms of best performance.

This study sought to determine public sentiments towards ore nickel export restriction in Indonesia that has been proclaimed since early January 2020.



<Figure 3> Analysis of Indonesian Perceptions on Nickel Export Restriction

As can be seen from the figure above, the majority of Indonesians support the nickel export restriction. On the first of January 2020, nickel ore with a grade below 1.7% is no longer allowed to be exported. The government announced this strategy to speed up the development of smelters, particularly those that produce nickel. As for the fundamental reason of the policy adoption is the limited reserves of Indonesia's nickel, which, if not managed properly,



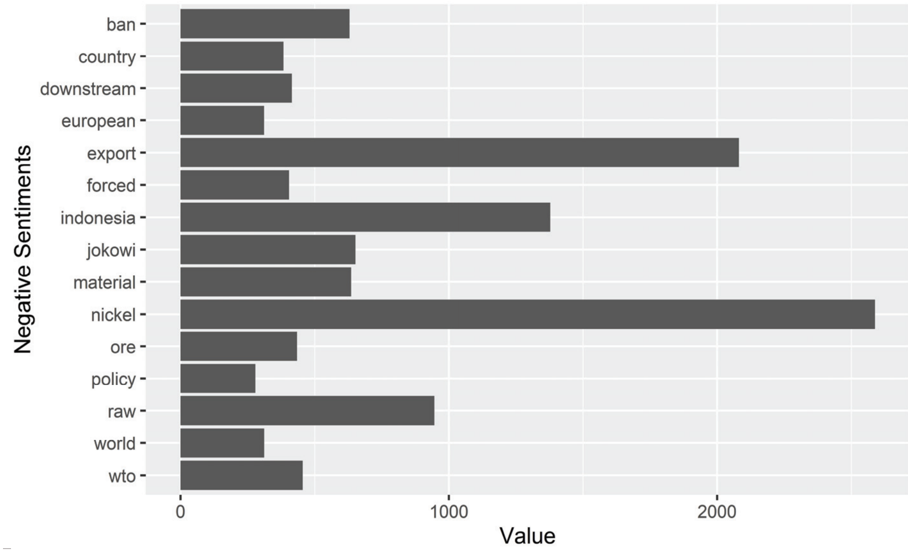
<Figure 4> Positive Sentiments Regarding Nickel Ore Export Restriction

can lead to scarcity in the next few years. It is expected that 698 million tons of current reserves can only ensure the supply of nickel ore for processing facilities for 7 years (assuming no additional reserves are discovered). Meanwhile, to meet the needs of refining facilities for about 40 years, probable nickel reserves of 2.8 billion tons still need improvements in altering aspects like accessibility, environmental permits, and suitable price. As a result, the government must take proactive measures to ensure that the reserves will last for the smelter's entire economic life. Additionally, the owned ore nickel reserves can be domestically refined and used as a raw material for electric batteries, negating the need to export them, thanks to the ongoing development of low-grade nickel management technology.

A more-detailed results of public opinions obtained from Twitter are presented in <Figure 4>. Closer inspection of the figure shows that positive sentiments regarding nickel export restriction focuses around industrial downstream and sustainable energy. This data is combined with other words commonly used by the public when discussing the nickel export ban from a positive perspective. These words include Jokowi, downstream, country, and resource. The combination of these words ultimately forms a public opinion that believes in Indonesia's resilience in the mining sector.

A nickel export prohibition is opposed by about 29.5% of the Indonesians. From <Figure 5>, we can see that most people who disagrees would focus on words like 'ban', 'forced', 'wto', and 'european.' A possible explanation for this might be a complaint, regarding the Indonesia's policy of nickel exports ban, that was initiated by The European Union (EU) to the World Trade Organization (WTO). President Jokowi's name also appeared in the negative dataset. This finding suggests that a public opinion was formed that almost rivaled the positive sentiment towards the issue. Some people who voiced their opinions on Twitter felt less in agreement with the nickel export ban policy, which they perceived as a policy that was 'forced' by the government.

<Table 2> display samples of the calculation of



<Figure 5> Negative Sentiments Regarding Nickel Ore Export Restriction

<Table 2> LDA Analysis

Topic0	('0.085*"nickel" + 0.057*"export" + 0.021*"jokowi" + 0.017*"raw" + 0.017*"trillion" + 0.017*"downstream" + 0.015*"rp" + 0.014*"china" + 0.013*"material" + 0.013*"country"')
Topic1	('0.196*"nickel" + 0.107*"indonesia" + 0.044*"exports" + 0.043*"jokowi" + 0.019*"raw" + 0.016*"downstream" + 0.012*"export" + 0.008*"world" + 0.006*"president" + 0.006*"government"'),
Topic2	('0.069*"nickel" + 0.016*"mining" + 0.010*"pt" + 0.009*"china" + 0.008*"smelter" + 0.008*"indonesia" + 0.007*"million" + 0.007*"sulawesi" + 0.006*"tons" + 0.006*"idr"'),

3 topics using LDA models. The table show the words related to each topic, with the top ten terms (words) listed for each topic. Each topic is associated with one or more documents in the group, with a mixing proportion determined by the occurrences of words per document. In topic 1, collection of words in table 5 shows that the topic is possibly refers to the positive view of the nickel export ban, because of the words such as, 'downstream' and its emphasis on the main figure of the current government, which indicates that the public has recognized the government's downstreaming policy as a product of the Jokowi administration.

Ⅴ. Discussion and implications

5.1. Discussion of Findings

Our study made several important findings. The first is that Twitter, indeed, was a powerful tool to conduct sentiment analysis. The range of Twitter users who voice their opinions on a given issue offers diverse perspectives, facilitating analysts' examination of the problem from various angles. Twitter's inclusive nature toward all sectors of society furthermore promotes a sense of vigilance and discernment among the community regarding different government policies. The growing number of Twitter users in Indonesia also shows the transition to a politically literate society. This finding agrees with previous research that points out Twitter has evolved into an influential networked environment of politically literate society. Based on our mined dataset, it can be inferred that each extracted sentiment represents a genuine reflection of public response to governmental policies. The number of public opinions expressed indicates that individuals recognize their right to hold and convey an opinion in the form of an assessment of government policies. Advancements in local freedom of expression also demonstrate Indonesia's ongoing commitment to upholding democracy.

Next important finding from our study is that regarding the nickel ore export restriction policy, The majority of Indonesians view this bold policy as the appropriate action for the local government to take. This correlates with previous research on nickel ore export restriction, where it is contend that the policy will likely benefit Indonesia's economic development, particularly by increasing the country's revenue from mining exports and become livelihood land of the income of communities living in nickel mining and smelter areas (Kurniawan et al., 2021; Soelistijo, 2013). Our findings explain, specifically, how the community also thinks that the downstreaming of the nickel industry is an appropriate step in the region's development efforts. Even, most local society welcomed the nickel downstreaming program and saw its economic benefits, owing to the fact that they obtained certain economic benefits from the nickel smelter, such as a program to bolster health care initiatives, social infrastructure, economic base diversification, and income growth.

As mentioned in the previous explanation, the fundamental reason of nickel export restrictions was to ensure that the industrial downstream in Indonesia could run smoothly while preserving the supply of ore nickels. It is apparent from the figure of positive sentiments that local citizens highly believed that the government policy to ban nickel export will hugely impact mining industrial in Indonesia, resulted in a successful effort to preserve ore nickel, sped up local smelters development that prompted jobs opportunities for local communities, and increase the output of indigenous mining products which will boost state revenues.

Another important finding is that the positive sentiments also centre on the word 'electric.' Surprisingly, local citizens of Indonesia saw nickel reserves not only as an Indonesian resource that must be safeguarded, but also as an alternative energy source. Moreover, the use of electric vehicles is becoming more popular worldwide, and nickel is a significant raw material used in the production of batteries. Indonesia is in a transitional period towards the use of renewable energy; therefore, it is not surprising that this alternative energy has become a hot topic of discussion among local communities. Following the implementation of the nickel ore export prohibition policy, investment in smelters and electric car battery companies continued to flood into the country. The overall expenditure for this smelting facility was $8 billion, but the realization has reached $6.3 billion in just six months since the nickel export embargo went into place. Hence, given the positive impact on the Indonesian people, it is not unexpected that the majority of Indonesians believe that President Jokowi's restriction on nickel exports is the best course of action for the welfare of society.

However, not only did we identify the positive sentiments of people's opinions regarding the nickel export ban, but we also observed the drawbacks of their viewpoints. Prior research of nickel ore exports prohibition stated that those who were directly affected by the nickel ore downstreaming policy were dissatisfied with the implementation of the environmental program, project's transportation management system, unfriendly staff behaviors, and vehicle quality. In addition, previous research has shown that some Indonesian mining companies profitability suffers as a result of a restriction or reduction in the volume of raw material exports (Ardianti and Lestari, 2023). To enhance understanding of the reasons behind the negative perception of the nickel downstream policy, we identified an additional factor towards local community's disapproval of nickel ore export restrictions that was based on the findings of this study: the apprehension of sanctions from the European Union and WTO against Indonesia. The trade dispute that started since the policy has been in effect since 2020 raises concerns for the public, especially as this series of policies could significantly strain Indonesia's relationship with the European Union. The European Union later filed a complaint with the World Trade Organization (WTO) against the policy of banning nickel exports. Due to the policy's violations of several GATT (General Agreement on Trade and Tariffs) articles from 1994, the WTO rejected Indonesia's defence in the case. Instead, the WTO panel advised Indonesia to act right away to fulfill its commitments under GATT 1994.

In other words, Indonesia was asked to remove the prohibition policy of nickel exports. Taken together, these results suggest that local citizens may felt that the policy of prohibiting nickel exports is a hasty measure. This perception emerged as a result of the dispute between EU and Indonesia. The frequent usage of the terms 'wto' and 'european' indicates that the Indonesian populace believes that this policy has a major potential to harm Indonesia's relations with various nations and other international organizations on a bilateral and multilateral basis. Not only does it have the potential to sour ties with other countries, but the Indonesians is also wary of penalties that will be imposed by the EU and WTO, which might have detrimental effects on Indonesia's international trading circumstances. For that reason, The Indonesian government must take deliberate measures to achieve a compromise between these two opposing viewpoints. Effective action must be taken in a few areas, including educating the public about the positive effects of the ban on the export of nickel ore, maintaining transparency in the administration of sanctions and the dispute settlements, preventing the spread of false information that could stoke social unrest in Indonesia, and creating jobs for the local population at built-in smelters. It is considered necessary for the government to pay enough attention to these measures, in order for this nickel export prohibition policy to be implemented successfully.

In particular, our findings highlight the importance of Twitter as a sentiment analysis channel which, if optimized, can be a very useful tool in the decision-making process for governments, as well as other organizations. Beside that, we have also analyzed the supportive and pessimistic sentiments towards the nickel export ban policy implemented during President Jokowi's term. Positive sentiment indicate support for Indonesia's efforts to enhance the value of its natural resources and create jobs within the country. Conversely, negative sentiment indicate concerns about disruptions to the global supply chain and potential economic consequences. It is imperative to avoid stereotypical descriptions regarding the positioning of Indonesia's efforts, as they might anonymize the complexities of the problem.

5.2. Limitations and Future Research Directions

Despite the study's substantial findings, what we discovered should be viewed in light of its limitations. To begin, we solely gathered real-time information from Twitter users. It would be beneficial to replicate the study across multiple social media platform to further examine the robustness of these findings. Another limitation that occurs is that our dataset is limited to 7070 tweets because this topic is not popular with most Indonesians. Only a few pay attention to and analyze President Joko Widodo's downstream program. However, due to the upcoming 2024 election in Indonesia, some candidates have begun discussing downstream programs. It is likely that more public opinions will emerge regarding downstream, particularly in December 2023, when presidential candidates engage in more intense debates and interactions with Indonesians than in previous months and years. Therefore, future research could collect Twitter data from December 2023 to February 2024, until the election is held, to obtain additional information on public perceptions of this downstream program. The large amount of public data commenting on downstream programs can be a good additional source to increase the accuracy of the ML and DL models that have been built.

Next, due to the fact that all of the components in this study were collected simultaneously and through the same instrument, which gathers tweets and comments about the nickel ore export ban throughout 2022, there is a possibility of common technique bias. Future research should collect longitudinal and objective data, and confirm the impact of the export ban legislation, especially on the indigenous community living near the smelter and companies involved in the Indonesian mining sector. And the last one, many distant places in Indonesia are still unfamiliar with Twitter. To determine whether the impact of the nickel ore export prohibition is genuinely felt by these community groups, future study ought to reach to many remote places affected by the development of nickel smelters, or even those who were financially affected (due to working in nickel ore mines).

5.3. Implications for Research and Practice

The research has potential implications for both research and practical applications. For future research, this work could contribute to the methodology of sentiment analysis by applying both traditional machine learning techniques (such as Support Vector Machines) and deep learning methods (like Long Short-Term Memory networks) to Twitter data. Comparing the performance of these methods provides insights into the effectiveness of different approaches. Next, the study's focus on sentiments related to nickel ore export restrictions under a specific political administration (President Jokowi's Administration in 2022) could provide valuable insights into public opinion regarding government policies and their potential economic impacts.

For the practical applications, The sentiment analysis findings may have implications for policymakers and government officials. Understanding public sentiment can inform decision-making processes related to trade policies, particularly in industries such as mining and export. Additionally, companies involved in the nickel industry or related sectors may gain practical insights from the sentiment analysis. It could help businesses gauge public perception and adjust strategies accordingly. This research is also likely to contribute to the risk management efforts of the company, in terms of understanding how public perceives export restrictions can guide communication strategies. Companies and governmental bodies can tailor their messaging to address concerns or capitalize on positive sentiments. Last but not least, the use of machine learning and deep learning techniques to analyze sentiments in real-world contexts demonstrates the practical applications of these technologies beyond academic research, where regularly analyzing public sentiment on platforms like Twitter can be a valuable tool for staying informed about public opinions and concerns, specifically in times of controversial policies or amidst huge risks.

Ⅵ. Conclusion

Despite the growing phenomenon of sentiment analysis using Twitter data, there is still a lack of research that focuses on the use of this textual data to formulate economic policy, particularly in the case of Indonesia's nickel ore export ban to Europe. Previous research has been dominated by the examination of this bold policy from a legal perspective, the new opportunity to be seized with value-added nickel, its impact on the Indonesian mining industry, the ongoing litigation, and the policy's impact on the global nickel market. Therefore, this study attempts to broaden the perspective on nickel ore export ban by using big data tools, namely sentiment analysis, to collect and analyze public opinion, which is expected to be a valuable asset in government policy formulation.

Our research highlighted varied sentiments from the Indonesians regarding nickel ore export restriction to Europe. Majority Indonesians agreed that this bold policy is the appropriate action for the government to take. The positive polarity emerged from the fundamental trust from local citizens to the government, where this provision to ban nickel export will hugely impact mining industrial in Indonesia, resulted in a successful effort to preserve ore nickel, sped up local smelters development that prompted jobs opportunities for local communities, and increase the output of indigenous mining products which will boost state revenues. Indonesians also saw nickel reserves not only as an important resource that must be safeguarded, but also as an alternative energy source. Moreover, the use of electric vehicles is becoming more popular worldwide, and nickel is a significant raw material used in the production of batteries, particularly the country is in the transition to renewable energy. Meanwhile, negative sentiments circled around concerns of the impact on trade dispute that happened between Indonesia and the European Union. It is understandable that some people might think that the government 'came on too strong' to implement this policy, as it could significantly strain Indonesia's relationship with the European Union and other countries as well.

Thus, our work contributes to current research by advancing the theoretical understanding of Twitter as a channel for sentiment analysis in government-citizen interactions to formulate a more acceptable policy formulation. This research also provided new insights to the field of International Relations, with the convergence of big data and the traditional perspective of IR, which could potentially generate new discourses. In addition to the theoretical contributions, this work also contributes to current practice by providing a framework for data analysis using machine learning and deep learning to serve as a valuable tool in formulating new policies.

<References>

[1] Ahmad, M., Aftab, S., Bashir, M. S., and Hameed, N. (2018). Sentiment analysis using SVM: A systematic literature review. *International Journal of Advanced Computer Science and Applications*, *9*(2), 182-188. https://doi.org/10.14569/IJACSA.2018.090226

[2] Ahuja, R., Chug, A., Kohli, S., Gupta, S., and Ahuja, P. (2019). The impact of features extraction on the sentiment analysis. *Procedia Computer Science*, *152*, 341-348. https://doi.org/10.1016/j.procs.2019.05.008

[3] Aladwani, A. M., and Dwivedi, Y. K. (2018). Towards a theory of SocioCitizenry: Quality anticipation, trust configuration, and approved adaptation of governmental social media. *International Journal of Information Management*, *43*(March), 261-272. https://doi.org/10.1016/j.ijinfomgt.2018.08.009

[4] Aljedaani, W., Rustam, F., Mkaouer, M. W., Ghallab, A., Rupapara, V., Washington, P. B., Lee, E., and Ashraf, I. (2022). Sentiment analysis on Twitter data integrating TextBlob and deep learning models: The case of US airline industry. *Knowledge-Based Systems*, *255*, 109780. https://doi.org/10.1016/j.knosys.2022.109780

[5] Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., Davis, S. J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., and Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics*, *191*, 104274. https://doi.org/10.1016/j.jpubeco.2020.104274

[6] Ardianti, R., and Lestari, W. D. (2023). Government policy regarding coal and nickel export ban the impact on the indonesian mining industry. *International Journal of Accounting, Management and Economic Research (IJAMER)*, *1*(1), 23-33.

[7] Blazquez, D., and Domenech, J. (2018). Big Data sources and methods for social and economic analyses. *Technological Forecasting and Social Change*, *130*, 99-113. https://doi.org/10.1016/j.techfore.2017.07.027

[8] Boon-Itt, S., and Skunkan, Y. (2020). Public perception of the COVID-19 pandemic on Twitter: Sentiment analysis and topic modeling study. *JMIR Public Health Surveill*, *6*(4), e21978. https://doi.org/10.2196/21978

[9] Cahyani, D. E., and Patasik, I. (2021). Performance comparison of tf-idf and word2vec models for emotion text classification. *Bulletin of Electrical Engineering and Informatics*, *10*(5), 2780-2788. https://doi.org/10.11591/eei.v10i5.3157

[10] Carracedo, P., Puertas, R., and Marti, L. (2021). Research lines on the impact of the COVID-19 pandemic on business. A text mining analysis. *Journal of Business Research*, *132*, 586-593. https://doi.org/10.1016/j.jbusres.2020.11.043

[11] Chen, L. C., Lee, C. M., and Chen, M. Y. (2020). Exploration of social media for sentiment analysis using deep learning. *Soft Computing*, *24*(11), 8187-8197. https://doi.org/10.1007/s00500-019-04402-8

[12] Chory, R. N., Nasrun, M., and Setianingsih, C. (2019). Sentiment analysis on user satisfaction level of mobile data services using Support Vector Machine (SVM) algorithm. In *Proceedings - 2018 IEEE International Conference on Internet of Things and Intelligence System, IOTAIS 2018* (pp. 194-200). https://doi.org/10.1109/IOTAIS.2018.8600884

[13] Day, M. Y., and Lin, Y. Da. (2017). Deep learning for sentiment analysis on google play consumer review. In *Proceedings - 2017 IEEE International Conference on Information Reuse and Integration, IRI 2017*, *2017-Janua* (pp. 382-388). https://doi.org/10.1109/IRI.2017.79

[14] Day, M. Y., and Teng, H. C. (2017). A study of deep learning to sentiment analysis on word of mouth of smart bracelet. In *Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2017* (pp. 763-770). https://doi.org/10.1145/3110025.3110129

[15] Devika, M. D., Sunitha, C., and Ganesh, A. (2016).

Sentiment analysis: A comparative study on different approaches. *Procedia Computer Science*, *87*, 44-49. https://doi.org/10.1016/j.procs.2016.05.124

[16] Duncombe, C. (2017). Twitter and transformative diplomacy: Social media and Iran–US relations. *International Affairs*, *93*(3), 545-562. https://doi.org/10.1093/ia/iix048

[17] Duncombe, C. (2019). The politics of Twitter: Emotions and the power of social media. *International Political Sociology*, *13*(4), 409-429. https://doi.org/10.1093/ips/olz013

[18] Elgendy, N., and Elragal, A. (2016). Big data analytics in support of the decision making process. In *Procedia Computer Science*, *100*, 1071-1084. https://doi.org/10.1016/j.procs.2016.09.251

[19] Georgiadou, E., Angelopoulos, S., and Drake, H. (2020). Big data analytics and international negotiations: Sentiment analysis of Brexit negotiating outcomes. *International Journal of Information Management*, *51*(November 2019). https://doi.org/10.1016/j.ijinfomgt.2019.102048

[20] Graham, T., Jackson, D., and Broersma, M. (2014). New platform, old habits? Candidates' use of Twitter during the 2010 British and Dutch general election campaigns. *New Media and Society*, *18*(5). https://doi.org/10.1177/1461444814546728

[21] Grčar, M., Cherepnalkoski, D., Mozetič, I., and Kralj Novak, P. (2017). Stance and influence of Twitter users regarding the Brexit referendum. *Computational Social Networks*, *4*(1). https://doi.org/10.1186/s40649-017-0042-6

[22] Grover, P., Kar, A. K., Dwivedi, Y. K., and Janssen, M. (2019). Polarization and acculturation in US Election 2016 outcomes - Can twitter analytics predict changes in voting preferences. *Technological Forecasting and Social Change*, *145*, 438-460. https://doi.org/10.1016/j.techfore.2018.09.009

[23] Grubmüller, V., Götsch, K., and Krieger, B. (2013). Social media analytics for future oriented policy making. *European Journal of Futures Research*, *1*(20), 1-9. https://doi.org/10.1007/s40309-013-0020-7

[24] Guerrero-Solé, F. (2018). Interactive behavior in political discussions on Twitter: Politicians, media, and citizens' patterns of interaction in the 2015 and 2016 electoral campaigns in Spain. *Social Media and Society*, *4*(4). https://doi.org/10.1177/2056305118808776

[25] Hall, W., Tinati, R., and Jennings, W. (2018). From brexit to trump: Social media's role in democracy. *Computer*, *51*(1), 18-27. https://doi.org/10.1109/MC.2018.1151005

[26] Han, K. X., Chien, W., Chiu, C. C., and Cheng, Y. T. (2020). Application of support vector machine (SVM) in the sentiment analysis of twitter dataset. *Applied Sciences (Switzerland)*, *10*(3). https://doi.org/10.3390/app10031125

[27] Hürlimann, M., Davis, B., Cortis, K., Freitas, A., and Fernández, S. (2016). A Twitter Sentiment Gold Standard for the Brexit Referendum. In *SEMANTiCS 2016: Proceedings of the 12th International Conference on Semantic Systems*. https://doi.org/10.1145/2993318.2993350

[28] Imran, A. S., Daudpota, S. M., Kastrati, Z., and Batra, R. (2020). Cross-cultural polarity and emotion detection using sentiment analysis and deep learning on covid-19 related tweets. *IEEE Access*, *8*, 181074-181090. https://doi.org/10.1109/ACCESS.2020.3027350

[29] International Labour Organization. (2022). *A Just Energy Transition in Southeast Asia: The Impacts of Coal Phase-Out on Jobs*. International Labour Organization.

[30] International Nickel Study Group. (2021). The World Nickel Factbook 2021. Retrieved from https://insg.org/wp-content/uploads/2022/02/publist_The-World-Nickel-Factbook-2021.pdf

[31] Kadhim, A. I. (2019). Term weighting for feature extraction on Twitter: A comparison between BM25 and TF-IDF. In *2019 International Conference on Advanced Science and Engineering, ICOASE 2019* (pp. 124-128). https://doi.org/10.1109/ICOASE.2019.8723825

[32] Krustiyati, A., and Christine, N. (2022). Analyzing

the lawsuit of the European Union over nickel ore export regulation in Indonesia. *Croatian International Relations Review, XXVIII*(89), 121-135. https://doi.org/10.2478/CIRR-2022-0007

[33] Kurniawan, A. R., Murayama, T., and Nishikizawa, S. (2021). Appraising affected community perceptions of implementing programs listed in the environmental impact statement: A case study of Nickel smelter in Indonesia. *The Extractive Industries and Society, 8*(1), 363-373. https://doi.org/10.1016/j.exis.2020.11.015

[34] Leelawat, N., Jariyapongpaiboon, S., Promjun, A., and Boonyarak, S. (2022). Twitter data sentiment analysis of tourism in Thailand during the COVID-19 pandemic using machine learning. *Heliyon, 8*(June). https://doi.org/10.1016/j.heliyon.2022.e10894

[35] Lim, B., Kim, H. S., and Park, J. (2021). Implicit interpretation of Indonesian export bans on LME nickel prices: Evidence from the announcement effect. *Risks, 9*(93). https://doi.org/10.3390/risks9050093

[36] Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. Morgan and Claypool Publishers.

[37] Lyu, Z., and Takikawa, H. (2022). Media framing and expression of anti-China sentiment in COVID-19-related news discourse: An analysis using deep learning methods. *Heliyon, 8*(8), e10419. https://doi.org/10.1016/j.heliyon.2022.e10419

[38] Ma, Y., Wang, M., and Li, X. (2022). Analysis of the characteristics and stability of the global complex nickel ore trade network. *Resources Policy, 79*, 103089. https://doi.org/10.1016/j.resourpol.2022.103089

[39] Medhat, W., Hassan, A., and Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal, 5*(4), 1093-1113. https://doi.org/10.1016/j.asej.2014.04.011

[40] Mohammed, S. H., and Al-Augby, S. (2020). LSA and LDA topic modeling classification: Comparison study on E-books. *Indonesian Journal of Electrical Engineering and Computer Science, 19*(1), 353-362. https://doi.org/10.11591/ijeecs.v19.i1.pp353-362

[41] Mourya, A. K., ShafqatUlAhsaan, and Kaur, H. (2020). Performance and evaluation of different kernels in support vector machine for text mining. In M. N. Mohanty and S. Das (Eds.), *Advances in Intelligent Computing and Communication* (pp. 264-271). Springer Singapore.

[42] Naing, H. W., Thwe, P., Mon, A. C., and Naw, N. (2019). Analyzing sentiment level of social media data based on SVM and Naïve Bayes algorithms. *Advances in Intelligent Systems and Computing, 744*, 68-76. https://doi.org/10.1007/978-981-13-0869-7_8

[43] Naseem, U., Razzak, I., Khushi, M., Eklund, P. W., and Kim, J. (2021). COVIDSenti: A large-scale benchmark Twitter data set for COVID-19 sentiment analysis. *IEEE Transactions on Computational Social Systems, 8*(4), 1003-1015. https://doi.org/10.1109/TCSS.2021.3051189

[44] Naw, N., and Mon, A. C. (2018). Social media data analysis in sentiment level by using support vector machine. *Journal of Pharmacognosy and Phytochemistry, 7*(1S), 609-613.

[45] Nemes, L., and Kiss, A. (2021). Social media sentiment analysis based on COVID-19. *Journal of Information and Telecommunication, 5*(1), 1-15. https://doi.org/10.1080/24751839.2020.1790793

[46] Neogi, A. S., Garg, K. A., Mishra, R. K., and Dwivedi, Y. K. (2021). Sentiment analysis and classification of Indian farmers' protest using twitter data. *International Journal of Information Management Data Insights, 1*(2). https://doi.org/10.1016/j.jjimei.2021.100019

[47] Nguyen, N. H., Nguyen, D. T. A., Ma, B., and Hu, J. (2022). The application of machine learning and deep learning in sport: predicting NBA players' performance and popularity. *Journal of Information and Telecommunication, 6*(2), 217-235. https://doi.org/10.1080/24751839.2021.1977066

[48] Pandyaswargo, A. H., Wibowo, A. D., Maghfiroh, M. F. N., Rezqita, A., and Onoda, H. (2021). The emerging electric vehicle and battery industry in Indonesia: Actions around the nickel ore export

ban and a SWOT analysis. *Batteries*, *7*(80). https://doi.org/10.3390/batteries7040080

[49] Pasupa, K., and Seneewong Na Ayutthaya, T. (2019). Thai sentiment analysis with deep learning techniques: A comparative study based on word embedding, POS-tag, and sentic features. *Sustainable Cities and Society*, *50*(December 2018), 101615. https://doi.org/10.1016/j.scs.2019.101615

[50] Prastyo, P. H., Sumi, A. S., Dian, A. W., and Permanasari, A. E. (2020). Tweets responding to the indonesian government's handling of COVID-19: Sentiment analysis using SVM with normalized poly kernel. *Journal of Information Systems Engineering and Business Intelligence*, *6*(2), 112. https://doi.org/10.20473/jisebi.6.2.112-122

[51] Pratama, B., Saputra, D. D., Novianti, D., and Purnamasari, E. P. (2019). Sentiment analysis of the Indonesian police mobile brigade corps based on Twitter posts using the SVM and NB methods. *Journal of Physics: Conference Series*, *1201*. https://doi.org/10.1088/1742-6596/1201/1/012038

[52] Prentice, C., Chen, J., and Stantic, B. (2020). Timed intervention in COVID-19 and panic buying. *Journal of Retailing and Consumer Services*, *57*, 102203. https://doi.org/10.1016/j.jretconser.2020.102203

[53] Rahardi, M., Aminuddin, A., Abdulloh, F. F., and Nugroho, R. A. (2022). Sentiment analysis of Covid-19 vaccination using support vector machine in Indonesia. *International Journal of Advanced Computer Science and Applications*, *13*(6), 534-539. https://doi.org/10.14569/IJACSA.2022.0130665

[54] Rahat, A. M., Kahir, A., and Masum, A. K. M. (2019). Comparison of Naive Bayes and SVM Algorithm based on Sentiment Analysis Using Review Dataset. In *Proceedings of the 2019 8th International Conference on System Modeling and Advancement in Research Trends, SMART 2019* (pp. 266-270). https://doi.org/10.1109/SMART46866.2019.9117512

[55] Razali, N. A. M., Malizan, N. A., Hasbullah, N. A., Wook, M., Zainuddin, N. M., Ishak, K. K., Ramli, S., and Sukardi, S. (2021). Opinion mining for national security: Techniques, domain applications, challenges and research opportunities. *Journal of Big Data*, *8*(1). https://doi.org/10.1186/s40537-021-00536-5

[56] Soelistijo, U. W. (2013). Prospect of potential nickel added value development in Indonesia. *Earth Science*, *2*(6), 129-138. https://doi.org/10.11648/j.earth.20130206.13

[57] Sontayasara, T., Jariyapongpaiboon, S., Promjun, A., Seelpipat, N., Saengtabtim, K., Tang, J., and Leelawat, N. (2021). Twitter sentiment analysis of bangkok tourism during covid-19 pandemic using support vector machine algorithm. *Journal of Disaster Research*, *16*(1), 24-30. https://doi.org/10.20965/jdr.2021.p0024

[58] Tai, K. S., Socher, R., and Manning, C. D. (2015). Improved semantic representations from tree-structured long short-Term memory networks. *ACL-IJCNLP 2015 - 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, Proceedings of the Conference*, *1*, 1556-1566. https://doi.org/10.3115/v1/p15-1150

[59] U.S. Geological Survey. (2022). Mineral Commodity Summaries 2022. U.S. Geological Survey, Retrieved from https://doi.org/10.3133/mcs2022

[60] Vijay, and Verma, P. (2022). Extremism detection on social media using SVM text classifier. *Journal of Pharmaceutical Negative Results*, *13*(7), 3748-3753. https://doi.org/10.47750/pnr.2022.13.S07.477

[61] Wankhade, M., Rao, A. C. S., and Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review, 55*(7). Springer Netherlands. https://doi.org/10.1007/s10462-022-10144-1

[62] Widiatedja, I. G. N. P. (2021). Indonesia's export ban on nickel ore: Does it violate the World Trade Organization (WTO) rules? *Journal of World Trade*, 667-696. http://www.kluwerlawonline.com/api/Product/CitationPDFURL?file=Journals%5CTRAD%5CTRAD2021028.pdf

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