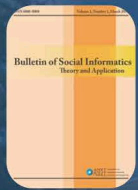
sinta.kemdikbud.go.id/journals/profile/4367

SINTA

Author Subjects Affiliations Sources FAQ WCU Registration Login

Get More with SINTA Insight

Go to Insight



BULLETIN OF SOCIAL INFORMATICS THEORY AND APPLICATION

ASSOCIATION FOR SCIENTIFIC COMPUTING ELECTRICAL AND ENGINEERING (ASCEE)

P-ISSN : E-ISSN : 26140047

0.717949	198	Sinta 2
Impact Factor	Google Citations	Current Acreditation

Google Scholar Garuda Website Editor URL

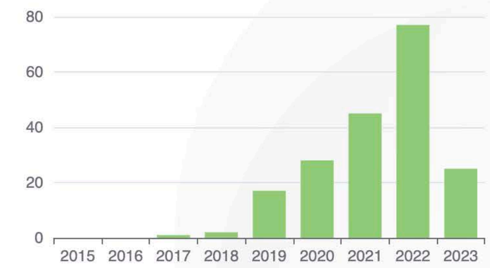
History Accreditation

2017	2018	2019	2020	2021	2022	2023

Garuda Google Scholar

Publication Not Found

Citation Per Year By Google Scholar



Journal By Google Scholar

	All	Since 2018
Citation	198	196
h-index	8	8
i10-index	5	5

592-Article Tex....docx okk.pdf export_verificat....xlsx E-Surat Waru bar....pdf Show All

Research on the Perspective of Internet Public Opinion in Social Media Twitter about Recession in Indonesia Using Sentiment Analysis

Fauzan Prasetyo Eka Putra
Universitas Madura

Fairuz Iqbal Maulana
Bina Nusantara University

Nawawi Muhammad Akbar
Law Science and Development , Postgraduate School, Airlangga University, Surabaya, Indonesia 60115

Keywords: sentiment analysis, twitter, perspective, indonesia, Recession

Abstract

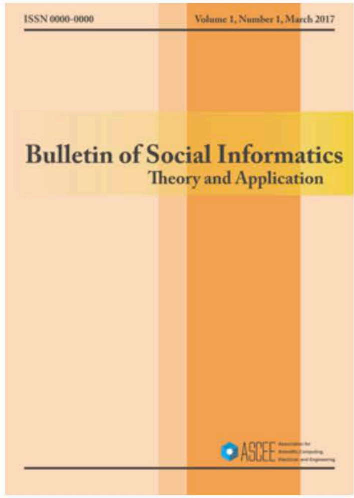
Twitter, as one of the most famous social media platforms, allows people to voice their views on various ideas, goods, and services. Large amounts

Published
2023-05-22

How to Cite
Eka Putra, F. P., Maulana, F. I., & Akbar , N. M. . (2023). Research on the Perspective of Internet Public Opinion in Social Media Twitter about Recession in Indonesia Using Sentiment Analysis. *Bulletin of Social Informatics Theory and Application*, *7*(1). Retrieved from https://pubs.ascee.org/index.php/businta/article/view/592

More Citation Formats

Issue



Research on the Perspective of Internet Public Opinion in Social Media Twitter about Recession in Indonesia Using Sentiment Analysis

Fauzan Prasetyo Eka Putra [a,1,*], Fairuz Iqbal Maulana [b,2], Nawawi Muhammad Akbar [c,3]

[a] Faculty Of Engineering, informatic program study , Panglegur, Pamekasan, Indonesia, 69313 (9pt)
[b] Department Computer Science Department, School of Computer Science, Bina Nusantara University, Jakarta, Indonesia 11480
[c] Master of Law Science and Development , Postgraduate School, Airlangga University, Surabaya, Indonesia 60115
[1] prasetyo@unira.ac.id*; [2] fairuz.maulana@binus.edu; [3] nawawi.muhammad.akbar-2021@pasca.unair.ac.id (9pt)
* corresponding author

ARTICLE INFO

Article history
Received March xx, 2023
Revised April xx, 2023
Accepted Mei xx, 2023

Keywords
Sentiment analysis
Twitter
Perspective
Indonesia
Recession

ABSTRACT (10PT)

Twitter, as one of the most famous social media platforms, allows people to voice their views on various ideas, goods, and services. Large amounts of data shared as tweets can be used to extract user opinion and provide useful input to better the standard of products and services. People's views of the recession can be tracked in real time using social media mood analysis based on Twitter data. As a result, pertinent organizations or governments can take preemptive measures to address disinformation and improper behavior associated with the impacts of the Recession. The goal of this study is to see if there is a link between how people feel about the recession on Twitter. Twitter posts tagged with "Recession" in 2023 were mined for this study's data collection. This study examines filtered tweets for general sentiment, feelings, word usage, and trends. According to the findings, , there were 94% sentiments neutral tweets, 4% sentiments positive tweets, and 2% is sentiments negative tweets. Tweets with moderate subjective valence gather in the center of the polarity scale (between -1 and +1), whereas tweets with strong subjective valence are distributed across the scale.

1. Introduction

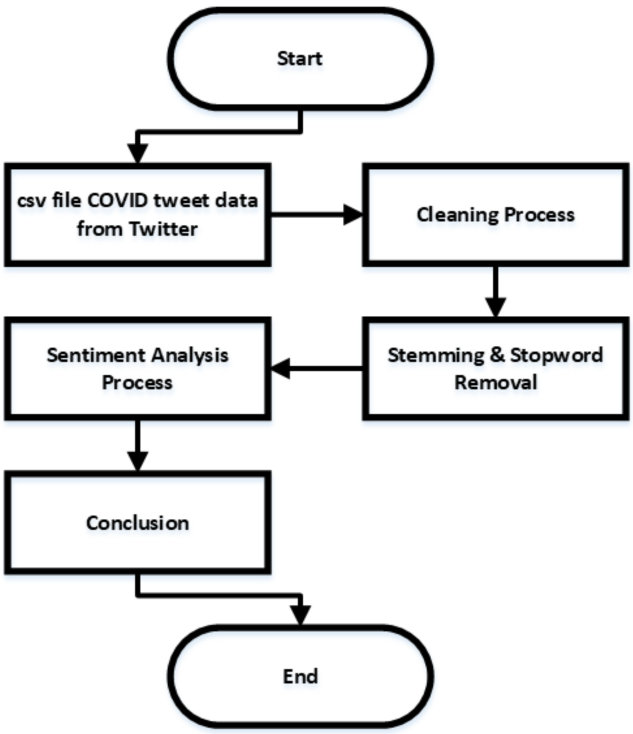
Text mining is a data mining method that can uncover buried pertinent information in text data sets. Text mining methods, such as mood analysis on Twitter data, can be applied to social media. Text mining methods are classified as information extraction, retrieval, document categorization, and clustering [1], [2]. Sentiment analysis is a form of text categorization that uses guided learning. There are three categories that can be applied to studies of emotion: positive, negative, and neutral. Technically, determining the mood class by determining the orientation value. A positive polarity value indicates positive emotion, whereas a negative polarity value indicates negative opinion. A polarity number of zero will indicate neutral feeling [3]. TextBlob is one of the tools that is commonly used in sentiment analysis. The TextBlob tool excels at mood analysis data processing in English [4]–[6]. However, text mining with Indonesian data sources still needs to improve due to the complexity of the structure in the Indonesian language. The Nazief and Adriani Algorithm is one of the text mining techniques used for Indonesian data analysis [7]. The modern era has seen a continuous development of text mining (TM) software. Artificial intelligence (AI) techniques have been the subject of numerous research articles in the medical field [8], [9], social survey [10], agriculture [11], including machine learning (ML) [12], online education [13], and predictive analytics [14].

Most existing studies use a method called machine learning, in which annotated data is used to analyze sentiment and the focus is on making models work better [13], [15]. This study, on the other hand, comes up with a new way to analyze sentiment by combining ML (machine learning) techniques with a model called TextBlob [2], [4], [5] that is based on a dictionary. Before, only a few methods, mostly machine learning models, were used to improve accuracy, and the characteristics of datasets were not taken into account. There is a chance that the annotations are wrong, because tweets that are marked as positive could actually be neutral or positive. Because of this, using these kinds of data with machine learning models can hurt how well the models work. With this assumption in mind, this study looks at how well TextBlob works for sentiment analysis compared to the original dataset. Despite previous attempts to improve model performance through hyperparameter settings, model design optimization, preprocessing pipelines, and feature extraction and selection techniques, the models did not improve significantly or at all.

The economic recession triggered by COVID-19 has piqued the interest of academics who want to learn more about its effect on various socioeconomic phenomena in people's lives. For example, examining the effect of the COVID-19 economic recession on elements of mental health, chronic illnesses, life span, and natural mortality [16] or how the recession affected the type of macroeconomic policy that should be implemented to lessen the effects of the recession [17]. Other studies that should be investigated of COVID-19 prediction that the pandemic could cause a worldwide food Recession [18]. Most of the research in this study focused on comprehensive Twitter sentiment analysis, focusing their research on the discussion regarding the Recession. Different topics are associated with various sentiment polarities, implying that sentiment analysis alone cannot disclose much without topic modeling. As a result, the researcher incorporates subject modeling into our study.

2. Method and Materials

Researchers obtained Tweet data from Twitter for this study by crawling on social media Twitter. The keywords for crawling used Indonesian input, namely "recession", and were taken on February 28, 2023. Aspects of topic modelling and sentiment analysis will be investigated at various points related to the Recession in this study. Figure 1 illustrates the method researchers have developed to analyze tweet data and find out the emotions of Twitter users. Researchers use Google Colab with the Python programming language to process the data. The first step is to collect data from Twitter by scrapping, then exporting it to a CSV format file; the next step, such as making the data in the file machine-readable through programming that has been made.



 ISSN 2614-0047

Fig. 1. Workflow of twitter opinion with Sentiment Analysis

The data in the CSV format file will go through a cleaning process, such as removing "RT, #, \, @, hyperlinks, and emoji, to leading and trailing whitespaces". After that, researchers will determine how users feel and label these opinions. Next, visualizations can be used to check sentiment on various elements.

3.1. Dataset

The information was acquired by scraping Tweets on Twitter social media using Python programming on Google Colab on February 28, 2023, and exporting as a CSV file. This file contains 1808 tweets from the last few weeks. Table 1 displays a subset of the CSV file data.

Table.1 Sample tweets

Datetime	Tweet ID	Tweet	Username
2023-02-27 22:22:30	1630332575637200896	Jujur ga punya kenangan interaksi secara langsung dengan event Beyond The Summit. Tapi, merasa sangat beruntung bisa interview GodZ di Maret 2021. Masih ga percaya Beyond The Summit kena efek resesi sehebat ini 💔	rosesagaming
2023-02-23 23:15:13	1628896290338914304	indonesia konsumtif tp bagus biar g resesi	adekhoky
2023-02-23 19:15:56	1628836072842199040	ujan ujan rebahan nonton drama uwu ❎ ujan ujan mikirin resesi global ✅ https://t.co/dZJ87kmUS6	iamlilboo

3.2. Data Preprocessing

Making sure our data is machine-readable is an essential component of data analysis. Machines, unlike people, can only handle binary data, making it challenging to comprehend human language, let alone images and films and analyzing 1 and 0 as data requires many stages. To be used, the data must first go through a data cleansing procedure, which includes turning the raw data into a computer-readable file. We must delete our extensive textual data collection, which comprises tweets, to remove any potential discrepancies. Unwanted information, such as URL connections, user comments, and unescaped HTML characters, is contained in the raw textual data and is not required for mood analysis. We straightforwardly sanitize data. We screen out irrelevant Twitter data during the pre-processing step. We deleted "RT, #, @, hyperlinks, and emoji, to preceding and following whitespaces" because our method of mood analysis does not require verifying extra information.

3.3. Sentiment Analysis

Semantic orientation evaluates texts' polarity and partiality, while sentiment analysis determines their affective tone. In this tweet, directional nouns and adverbs show logical flow. Adverbs divided by words determine emotional direction. Developers use TextBlob to analyze Twitter data and opinion. TextBlob ranks tweets numerically. TextBlob offers text hash tags, polarity, and opinion. Polarity is [-1.1], where -1 indicates negative emotion and 1 signifies optimism. Negative words become negative figures. Human experience is 0–1. A tweet's biased grade shows how much is opinion and how much is fact. "Polarity" describes how deeply people feel about views. Results may be good or bad. A person or entity deeply moved by good feelings like admiration, faith, or love will naturally adopt a certain worldview. Subjectivity is a person's connection to something. Regardless of others' opinions, emotional commitment and unique contact with the item are key.

Table.2 Sample sentiment analysis based on polarity and subjectivity score

Tweet	Polarity Score	Subjectivity Score	Sentiment
"Jujur ga punya kenangan interaksi secara langsung dengan event Beyond The Summit. Tapi, merasa sangat beruntung bisa interview GodZ di Maret 2021. Masih ga percaya Beyond The Summit kena efek resesi sehebat ini"	0.00	0.00	Neutral

Tweet	Polarity Score	Subjectivity Score	Sentiment
"Terindikasi & disinyalir bahkan banyak yg terpaksa menjual aset2nya (tansh, ruko, toko, kendaraan, ternak, kayu, dll) untuk mendapatkan dana segar. Banyak kredit bank yg macet dibekukan krn Kondisi yg memaksa. Sisi lain sibuk poksan-paksin & propaganda idu resesi ekonomi global"	-0.05	0.05	Negative
"G i truly did the best i could."	1.00	0.03	Positive

3. Result and Discussion

The results show that from the data file used, an average of more than 1699 tweets shows a neutral sentiment. Whereas for positive results, around 72 tweets were obtained, and the rest were negative sentiments, as shown in figure 2. Of the thousand tweets taken, there were 94% sentiments neutral tweets, 4% sentiments positive tweets, and 2% is sentiments negative tweets.

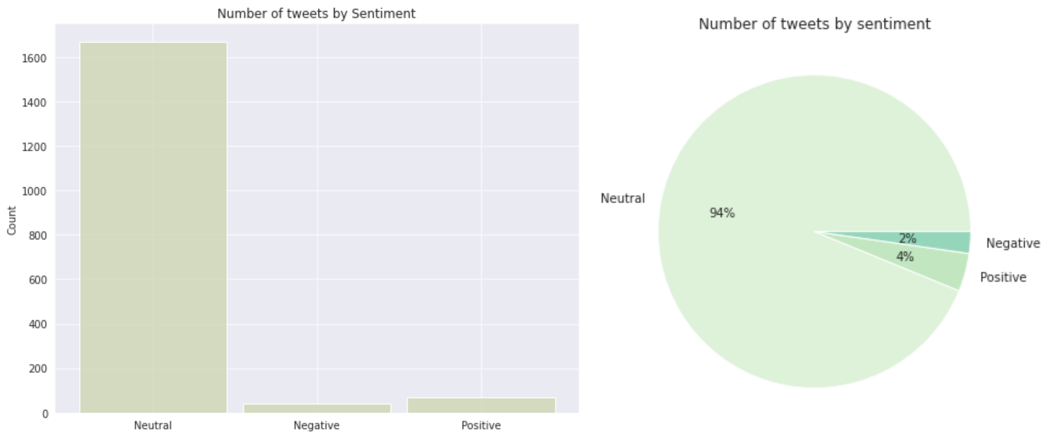


Fig. 2. Bar plot and pie plot of Sentiment Analysis

Then, the researcher wants to know the visualization of the word cloud based on the keyword recession and the data files obtained. Figure 3 depicts a word cloud made up of filtered tweets about the term recession. A word cloud is a graphical depiction of a data collection that emphasizes the regularity with which a specific term or sentence is used.

Fig. 3. Word cloud of tweet posts related to Recession

As shown in figures 4 and 5, the terms in the cloud collectively reflect the most frequently used words. A bigger font size indicates that the term is stated more frequently than a smaller font size. In summary, the word cloud can wrap up Twitter discussions about the keyword Recession. It can also help us comprehend what a recession is. Our filtered tweet word cloud frequently discovers instances

ISSN 2614-0047

of Indonesian and Turkish that occurred just before this tweet was crawled, as well as many other terms.

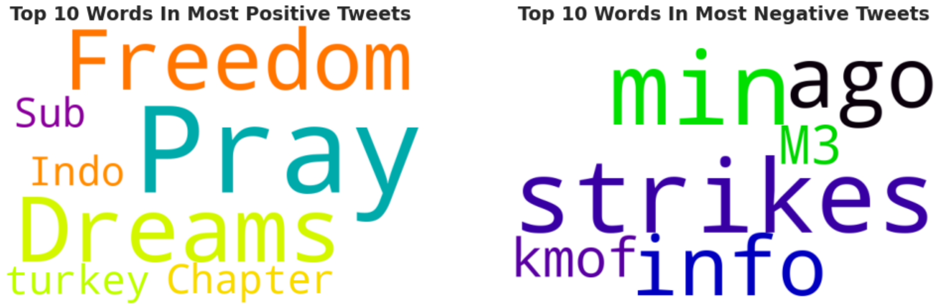


Fig. 4. Word cloud of tweet posts with top 10 Words in the most positif and negatif tweets

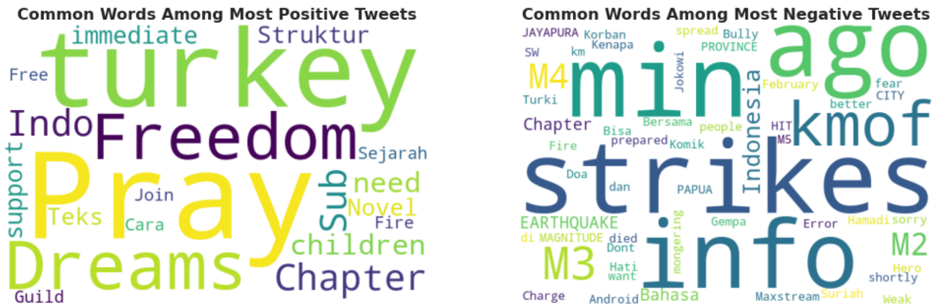


Fig. 5. Word cloud of tweet posts with common Words among most positif and negatif tweets

Next, the researcher wants to measure polarity and subjectivity, as in formula 1. The polarity of a tweet is determined by adding the numbers of the chosen characteristics to the message. Each tweet is given a rating based on the following criteria:

$$PolarityScore(tweet) = \sum featurevalue(tweet_i) \quad (1)$$

Figure 6 is based on the subjectivity and polarity values from the data file, which are displayed as polarity and subjectivity plots for every tweet ever sent. The blue color represents neutral sentiment, while the green color represents negative sentiment, and the yellow color represents positive sentiment. Positive sentiment is more prevalent than unfavorable sentiment across the globe. This indicates that our tweet collection has a wide subjective range, with the bulk of tweets lying on the [-1.00, 1.00] polarity scale (negative or positive).

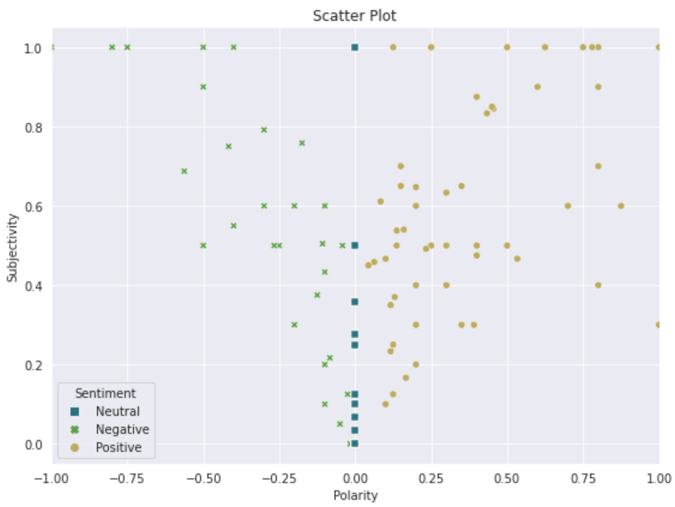


Fig. 6. Plotting Scatter Graph between Polarity and Subjectivity

ISSN 2614-0047

A correlation heatmap is a graphical depiction of a data set's correlation matrix between sets of factors. The association value is represented as a hue in the heat map, with each cell representing a set of factors. The heatmap in the Figure 7 represents a symmetric grid with correlation values ranging from -1 to 1, where -1 represents a perfect negative correlation, 0 represents no correlation, and 1 represents a perfect positive correlation. The strength and orientation of the correlation value are reflected in the cell colors, with warmer colors showing positive correlations and colder colors signaling negative correlations (such as blue and green). The darker the color, the stronger the link.

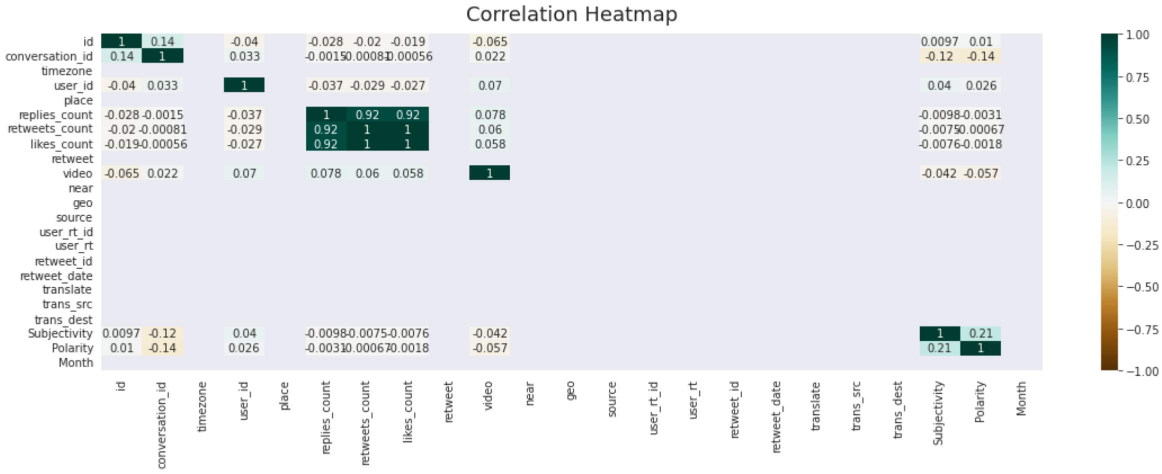


Fig. 7. Heatmap of correlations based on tweets mentioning the recession

Furthermore, the scholar notices that some variables have a strong positive connection, whereas others have a strong negative correlation. Heat maps can help you find patterns and connections in data sets, which can help you make data-driven choices or create predictive models.

Researchers gathered and examined tweets about the keyword Recession Tweets in Indonesian for this study to assess its prevalence and effect. According to the findings, different people have expressed an interest in Recession Tweets, both directly and through the media. Different social media sites continue to make it easier to spread Recession Tweet statistics. As a result, we require cutting-edge computational tools and methods to rapidly evaluate massive amounts of data. Sentiment analysis was created to combat the spread of misleading information on social media. Consumer insights will be helpful for several sectors to consider when developing new policies. Because of the large quantity of data accessible on social media sites such as Twitter, there is an increasing need for a systematic and effective strategy for analyzing tweets. This study will help a wide range of industries because it provides a snapshot of the facts on the ground, which is essential when pushing for legislative or regulatory changes.

4. Conclusion

Based on Twitter statistics in Indonesian, this research examines social media sentiment with the keyword Recession. According to this study, popular opinion on Twitter about the recession is overwhelmingly neutral. This study classified Twitter using text blobs, and the researchers successfully displayed data using a word cloud. With 1808 tweets collected, the sentiment study yielded 94% indifferent sentiment, 4% positive sentiment, and 2% negative sentiment. This study shows that opinion analysis on social media can be used to track recession trends in real-time. This finding, hopefully, will aid future mathematical modeling and data analysis research, particularly large-scale data processing by tracking responses and public statements via social media, particularly Twitter, using sentiment analysis.

Acknowledgment

We would like to thank everyone who has helped and backed our study on "Research on the Perspective of Internet Public Opinion in Social Media Twitter about Recession in Indonesia Using Sentiment Analysis". We would like to express our heartfelt gratitude to our supervisor for their invaluable guidance and support, to the participants who provided us with data and insights, to the research assistants and technical support team for their expertise and assistance, and to our friends and family for their unwavering support throughout the research process. We are extremely grateful for everyone's efforts, which made this study feasible.

References

[1] L. Feng, Y. K. Chiam, and S. K. Lo, "Text-Mining Techniques and Tools for Systematic Literature Reviews: A Systematic Literature Review," in *2017 24th Asia-Pacific Software Engineering Conference (APSEC)*, Dec. 2017, pp. 41–50, doi: 10.1109/APSEC.2017.10.

[2] R. Bose, S. Aithal, and S. Roy, "Sentiment Analysis on the Basis of Tweeter Comments of Application of Drugs by Customary Language Toolkit and TextBlob Opinions of Distinct Countries," *Int. J. Emerg. Trends Eng. Res.*, vol. 8, pp. 3684–3696, 2020, doi: 10.30534/ijeter/2020/129872020.

[3] M. Arora and V. Kansal, "Character level embedding with deep convolutional neural network for text normalization of unstructured data for Twitter sentiment analysis," *Soc. Netw. Anal. Min.*, vol. 9, no. 1, p. 12, Dec. 2019, doi: 10.1007/s13278-019-0557-y.

[4] R. Hermansyah and R. Sarno, "Sentiment Analysis about Product and Service Evaluation of PT Telekomunikasi Indonesia Tbk from Tweets Using TextBlob, Naive Bayes & K-NN Method," in *2020 International Seminar on Application for Technology of Information and Communication (iSemantic)*, Sep. 2020, pp. 511–516, doi: 10.1109/iSemantic50169.2020.9234238.

[5] W. Aljedaani *et al.*, "Sentiment analysis on Twitter data integrating TextBlob and deep learning models: The case of US airline industry," *Knowledge-Based Syst.*, vol. 255, p. 109780, Nov. 2022, doi: 10.1016/j.knosys.2022.109780.

[6] S. Zahoor and R. Rohilla, "Twitter Sentiment Analysis Using Lexical or Rule Based Approach: A Case Study," in *2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, Jun. 2020, pp. 537–542, doi: 10.1109/ICRITO48877.2020.9197910.

[7] D. Soyusiawaty, A. H. S. Jones, and N. L. Lestariw, "The Stemming Application on Affixed Javanese Words by using Nazief and Adriani Algorithm," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 771, no. 1, p. 012026, Mar. 2020, doi: 10.1088/1757-899X/771/1/012026.

[8] S. S. Sohail, M. M. Khan, and M. A. Alam, "An Analysis of Twitter Users From The Perspective of Their Behavior, Language, Region and Development Indices -- A Study of 80 Million Tweets," May 2021, [Online]. Available: http://arxiv.org/abs/2105.10245.

[9] S. Das and A. K. Kolya, "Predicting the pandemic: sentiment evaluation and predictive analysis from large-scale tweets on Covid-19 by deep convolutional neural network," *Evol. Intell.*, vol. 15, no. 3, pp. 1913–1934, 2022, doi: 10.1007/s12065-021-00598-7.

[10] M. Lepelaar *et al.*, "Sentiment Analysis of Social Survey Data for Local City Councils," *J. Sens. Actuator Networks*, vol. 11, no. 1, 2022, doi: 10.3390/jsan11010007.

[11] A. S. Neogi, K. A. Garg, R. K. Mishra, and Y. K. Dwivedi, "Sentiment analysis and classification of Indian farmers' protest using twitter data," *Int. J. Inf. Manag. Data Insights*, vol. 1, no. 2, p. 100019, 2021, doi: 10.1016/j.jjimei.2021.100019.

[12] N. Leelawat *et al.*, "Twitter data sentiment analysis of tourism in Thailand during the COVID-19 pandemic using machine learning," *Heliyon*, vol. 8, no. 10, p. e10894, 2022, doi: 10.1016/j.heliyon.2022.e10894.

[13] M. Mujahid *et al.*, "Sentiment Analysis and Topic Modeling on Tweets about Online Education during COVID-19," *Appl. Sci.*, vol. 11, no. 18, 2021, doi: 10.3390/app11188438.

[14] N. Chintalapudi, G. Battineni, M. Di Canio, G. G. Sagaro, and F. Amenta, "Text mining with sentiment analysis on seafarers' medical documents," *Int. J. Inf. Manag. Data Insights*, vol. 1, no. 1, p. 100005, 2021, doi: 10.1016/j.jjimei.2020.100005.

[15] M. Umer, I. Ashraf, A. Mehmood, S. Kumari, S. Ullah, and G. Sang Choi, "Sentiment analysis of tweets using a unified convolutional neural network-long short-term memory network model," *Comput. Intell.*, vol. 37, no. 1, pp. 409–434, 2021, doi: https://doi.org/10.1111/coin.12415.

[16] M. H. Brenner, "Will There Be an Epidemic of Corollary Illnesses Linked to a COVID-19-Related

Recession?," *American journal of public health*, vol. 110, no. 7. United States, pp. 974–975, Jul. 2020, doi: 10.2105/AJPH.2020.305724.

[17] H. Chernick, D. Copeland, and A. Reschovsky, "The Fiscal Effects of the COVID-19 Pandemic on Cities: An Initial Assessment," *Natl. Tax J.*, vol. 73, pp. 699–732, 2020, doi: 10.17310/ntj.2020.3.04.

[18] S. Goetz, C. Schmidt, L. Chase, and J. Kolodinsky, "Americans' Food Spending Patterns Explain Devastating Impact of COVID-19 Lockdowns on Agriculture," *J. Agric. Food Syst. Community Dev.*, vol. 9, no. 3, pp. 31–33, May 2020, doi: 10.5304/jafscd.2020.093.033.