Research Article GU J Sci 37(4): 1707-1716 (2024) DOI: 10.35378/gujs.1424742

Gazi University

Journal of Science

http://dergipark.gov.tr/gujs

Implementation of Text Mining to Detect Emotions of Fuel Price Increase using BERT-LSTM Methods

Pungkas SUBARKAH[1, *], Hasri Akbar Awal ROZAQ[2], Primandani ARSI[1], Siti Alvi SHOLIKHATIN[3], Riyanto RIYANTO[1], Hendra MARCOS[1]

[1]*Amikom Purwokerto University, Faculty of Computer Science, Purwokerto, Indonesia*
[2]*Gazi University, Graduate School of Informatics, Department of Computer Science, Ankara, Türkiye*
[3]*Amikom Purwokerto University, Faculty of Business and Social Sciences, Purwokerto, Indonesia*

Highlights

- This paper focuses on the classification process for detecting emotions related to fuel price.
- A hybrid approach is proposed for classification text mining in the study.
- An exact and more efficient classification accuracy was obtained.

Article Info

Received: 23 Jan 2024
Accepted: 03 Jun 2024

Keywords

BERT
Emotion
Fuel Price
LSTM
Oil

Abstract

Fuel is crucial for everyday life, especially as a primary source of transportation fueled by oil. In early April 2022, Indonesia experienced a significant event that deeply affected its populace: a surge in fuel prices. Addressing this pressing issue, this study employs emotion classification utilizing BERT and LSTM methods on social media data, particularly from platforms like YouTube, to categorize emotional responses to governmental decisions. This research aims to classify social media discourse surrounding fuel-related topics, notably the increases in fuel prices. The highest accuracy, at 95%, was achieved with oversampling techniques, contrasting with a mere 47% accuracy without oversampling. Surprisingly, experiments indicate that employing oversampling and BERT for emotion classification results in reduced accuracy during testing phases.

1. INTRODUCTION

Fuel is an essential element in everyday life. It is used in transportation, thus affecting mobilization. Fuel has become a necessity for people, especially in Indonesia, and plays an essential role in the operation of businesses or companies. Gasoline – one of the most used fuel oils – significantly impacts people's economic activities. This becomes a factor of change that must be considered when assessing changes in primary commodity prices [1-3]. In early April 2022, there was a topic that caused an uproar among Indonesians: the increase in the price of fuel oil (BBM). Since Indonesians have faced the same situation in previous years, fuel price increases have become common. The rise in fuel prices increases the strengths and weaknesses of society, especially among small communities that consume a disproportionate amount of fuel [4]. Detik.com reports attributing the fuel price surge to the nation's hefty subsidy burden and the misdirected allocation of subsidies, prompting the government to rethink its subsidy policies.

A CNBC Indonesia.com report, citing a broadcast from the Presidential Secretariat's YouTube account introduced by Finance Minister Sri Mulyani Indrawati, explains that the sharp rise in world oil prices has prompted the government to increase the large subsidies previously given for oil to provide social assistance. However, the main reason lies in calculating world oil prices by the national budget. Still, Indonesia's status is not an oil supplier but an oil importer, and it isn't easy to meet the development budget [5]. The community felt the impact of the increase in fuel prices. The increase in fuel has a natural effect

*Corresponding author, e-mail: subarkah@amikompurwokerto.ac.id

on macroeconomic conditions. This can be seen from the decline in gross domestic product, increased unemployment, and accelerated inflation [6]. The increase in fuel prices also triggered a rise in the price of necessities. This is due to increased production costs, thus increasing total costs and causing an increase in production costs [7]. Impacts like this reduce people's purchasing power, hamper the economy, and lead to a decline in the country's economy.

News about increased fuel consumption is inseparable from information technology's role in disseminating information worldwide. One of the platforms used to share information is YouTube. YouTube is the largest video platform in the world, and around 1.5 billion people worldwide were YouTube users in 2018 [8]. YouTube is also a social media that can provide education [9]. According to a survey conducted by Hootsuite (we are social) in January 2021, 94% of internet users visit YouTube. YouTube is designed to show videos and to comment on them. This can be a channel for opinions that can trigger conflicts spread through the YouTube platform. The increase in fuel prices has led to the expression of emotions in the form of communication, such as in writing, which is called emotion [10]. There are many types of emotions. According to research [11,12], humans have emotions: happiness, sadness, anger, surprise, disgust, and fear. Understanding emotions helps to understand people's tendencies in the psychological field and even decision-making [13].

Several methods can be used to understand and analyze emotions, one of which uses the BERT algorithm, which is effective for identifying and analyzing the mental health of social media user posts. Combining this method with LSTM will produce good accuracy and performance when creating the system [14]. Furthermore, detailing the data labeling and preprocessing stages enriches the methodological transparency of the study, ensuring rigor and reproducibility in the research process. Information about the data collected comes from several YouTube reviews using text mining methods. Users can express emotions that can be expressed in text [15]. Paramuda P. Insan and Kusrani researched emotion classification in 2021 using the ID3 and KNN methods on emotion classification on news datasets, resulting in better ID3 usage of 89.11% while KNN was 71.25%. Research conducted by Alia Sri Rezki 2021 by classifying emotions on Twitter resulted in an accuracy of 91.04% [16]. Furthermore, research conducted by [14] Predicting mental health using the BERT and LSTM methods resulted in an accuracy of 98%.

Based on the problems described, emotion classification research with BERT and LSTM methods by taking social media data on YouTube to classify types of emotions based on public response to government decisions from research [17,18] and taking from research [11] The emotions used in the study are angry, sad, afraid, happy, and surprised. This research is expected to help predict if there is new data to be grouped based on the type of emotion and immediately get the results.

2. MATERIALS METHOD

The process of creating an emotion detection system with BERT and LSTM can be shown in Figure 1. This research first conducts retrieval by taking it in a verified channel.

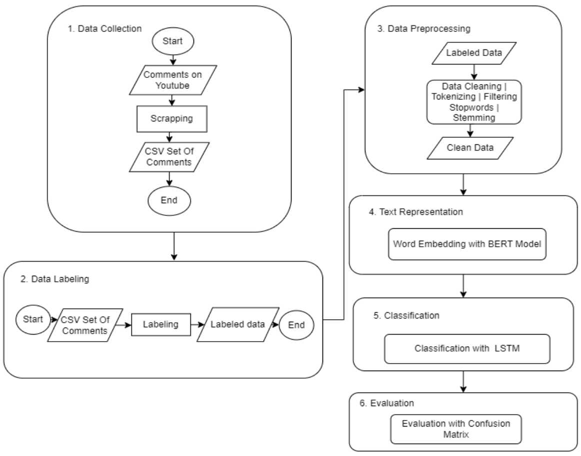

Figure 1. *Methods Flow*

2.1. Data Collection

Data collection is intended to find data on the internet. This research retrieves data from verified YouTube comments on channels. We used the YouTube API to connect data retrieval with the search topic of fuel increase news announced on September 3, which was broadcast on KompasTV, CNN, CNBC, and MetroTV channels. The data from the scrapping results include name, comment, time, and number of replies.

2.2. Data Preprocessing

Before the data is managed, it must first go through several stages of data cleaning that aim to eliminate noisy data that is not needed [19,20]. This research uses Python and several libraries to organize language processing using the Natural Language Toolkit (NLTK). The application is open-source, meaning the source code is publicly available and can be accessed, modified, and distributed by anyone. The first is the cleaning stage, followed by several other stages.

- Data Cleaning: data cleaning is a process to remove punctuation, tags, and symbols, and after that, all documents are converted to lower case or what can be called the case folding process [14].
- Tokenization: the data that has been processed before is then tokenized, which aims to separate the text into several tokens or terms that are used to find a pattern that will be taken as input for the following [14].
- Filtering Stopword: a stage to filter words that will not impact classifying a text and will only cause noise [19]. In this research, we remove stopwords using a stopword list from NLTK with an Indonesian stopword list.
- Stemming: Stemming is a process of changing words to their root form and has a short text with words already in their basic form [19,21].

2.3. Text Representation

Text Representation is also known as feature extraction, which converts text into a vector with an actual or numeric value and can also increase accuracy and shorten learning time [19], [21]. Many methods are used in word embedding or converting word characters into vectors, such as Word2Vect, binary encoding, and other models. Our research uses the BERT method to perform text representation on the corpus we collected.

The Bidirectional Encoder Representations for Transformers (BERT) model was proposed and published by Google Research [22]. BERT uses the transformer architecture and an attention mechanism that finds contextual contacts between words; each output element is connected to each input element, and element weights are dynamically calculated based on the relationship between elements [22]. Current NLP models can mostly only read text sequentially, either from left to proper to left, but not at once [21]. BERT uses two schemas to capture the contextual meaning of words in both the left and right directions [21]. Using BERT in an NLP system has slightly improved the result [23].

2.4. Classification with Long Short-Term Memory (LSTM)

In this research, we use deep learning with the LSTM as an algorithm model for data training. Long-Short Term Memory Networks (LSTM) modify recurrent neural networks or RNN [24]. LSTMs exist to fill the gap where RNNs cannot predict words based on long-stored past information [25]. In general, the RNN model with LSTM is more effective in overcoming the problem of sequence information fading when the text sequence information is very long [24]. The LSTM method is used to classify data over time by storing it in memory cells. The information collected by the LSTM algorithm is stored in cells, and memory operations are performed by components called gates. There are four components in the LSTM architecture: the forget gate, the input gate, the cell state, and the output gate [24].

Forget gate: to remove information no longer needed in the cell. At this stage, the binary output of the two inputs, x(t), and the previous cell output, h(t-1), are evaluated, multiplied by the weight matrix, added to the bias value, and passed on to the activation function to produce the binary output [24]. The detailed formula is shown in (1) below

$$a_{\emptyset}^{t} = \sum_{i=1}^{I} w_{i\emptyset} x_i^t + \sum_{h=1\ b_l^t = f(a_{\emptyset}^t)}^{H} w_{h\emptyset} b_h^{t-1} + \sum_{c=1}^{C} w_{c\emptyset} s_C^{t-1}. \quad (1)$$

Input Gate: The input gate does add charge information to the cell state. The information is set using a sigmoid function, which will filter the value to be stored. This process is like the forget gate that takes input h(t-1) and x(t) [24]. The details of the formula can be shown (2) below

$$a_l^t = \sum_{i=1}^{I} w_{il} x_i^t + \sum_{h=1\ b_l^t = f(a_l^t)}^{H} w_{hl} b_h^{t-1} + \sum_{c=1}^{C} w_{cl} s_C^{t-1}\ . \quad (2)$$

Output gate: responsible for extracting useful information from the current cell state and presenting it as an output value [24]. The detailed formula can be shown (3) below

$$a_l^t = \sum_{i=1}^{I} w_{iw} x_i^t + \sum_{h=1\ b_w^t = f(a_w^t)}^{H} w_{hw} b_h^{t-1} + \sum_{c=1}^{C} w_{cw} s_C^{t-1}\ . \quad (3)$$

2.5. Evaluation

When the system has been trained, it is necessary to monitor the performance of the system created to determine the superiority of the proposed method and to see the performance of the system created so that the system can be evaluated and developed again so that it can become a better system [26]. In evaluating our research, we use confidence measures as equations to calculate accuracy, recall, and precision formulated below

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$Precision = \frac{TP}{TP+FP}\ . \quad (6)$$

In the performance evaluation of classification models, the confusion matrix is an essential tool to understand the extent to which the model can predict correctly and identify the types of errors that may occur. True Positive (TP) reflects the number of instances correctly predicted as positive in this matrix. At the same time, a False Positive (FP) indicates the number of cases that should be negative but were predicted as positive. On the other hand, False Negative (FN) reflects the number of cases that should be positive but were predicted as negative, and True Negative (TN) indicates the number of cases that were correctly predicted as negative [27]. Through these values, we can calculate evaluation metrics such as accuracy, precision, and recall, which provide a more in-depth view of the strengths and weaknesses of the model in the specific context of the classification task.

Metrics such as accuracy, precision, and recall offer valuable insights in the performance evaluation of classification models [28]. Accuracy provides an overview of the model's ability to classify data correctly. However, when the evaluated classes are unbalanced, accuracy can be less informative. Precision, on the other hand, highlights how well the model avoids giving false positive predictions. This metric is beneficial when the cost of false positives is high. Recall, or sensitivity, provides information about the model's ability to detect all true positive instances. This is particularly important in cases where the error of not detecting a positive instance is considered more harmful [29]. By understanding and utilizing these three metrics, classification modeling can be optimized according to the needs and context of the problem.

3. RESULTS AND DISCUSSION

3.1. Data Scraping

The first stage of this research is scraping data for data collection as research material is public emotion. Data is taken from user comments on verified Indonesian news YouTube videos discussing the increase in fuel prices in Indonesia. The data was taken on December 11, 2022. The data scraping process is shown in Table 1.

Table 1. *Data Scraping Results*

Name	Comment	Time
Tjah ndeso	Mana pak sampai detik ini gak ada bantuan untuk ojek online??	2022-10-21T04:15:17Z
Aisyah Wulandari	Piye sih pak jokowi, bbm naik naiķ, pqdqhql itu artinya rakyat semakin menderita, karena harga2 barang lain pasti mèlonjak, rakyat semakin sulit cari uang, gaji/upah ajeg, rakyat Indonesia pasti tambah banyak yang miskin.	2022-10-11T11:20:47Z
Kampung AURi TanjakaN DKI	Y Allah BBm naik Rakyak miskin pada Kelaparan..cari buat makan aja susah..	2022-09-26T06:11:58Z

Based on table 1. There are three columns: Name, Comment, and Time, taken from YouTube user comments. Data were obtained from 6 different YouTube videos with the same topic of discussion: fuel price increases, totaling 1862 comments. Data is retrieved using the API client library.

3.2. Data Labelling

In this process, polarity is given to the dataset. Grouping using the manual labeling method was done by two people and cross-checked again. The labeling results are shown in Table 2.

Table 2. *Data Labelling Results*

Name	Comment	Time
Tjah ndeso	Mana pak sampai detik ini gak ada bantuan untuk ojek online??	2022-10-21T04:15:17Z
Aisyah Wulandari	Piye sih pak jokowi, bbm naik naiķ, pqdqhql itu artinya rakyat semakin menderita, karena harga2 barang lain pasti mèlonjak, rakyat semakin sulit cari uang, gaji/upah ajeg, rakyat Indonesia pasti tambah banyak yang miskin.	2022-10-11T11:20:47Z
Kampung AURi TanjakaN DKI	Y Allah BBm naik Rakyak miskin pada Kelaparan..cari buat makan aja susah..	2022-09-26T06:11:58Z

Labeling is done manually by dividing the label into several emotion classes. The labeling results are shown in Figure 2.

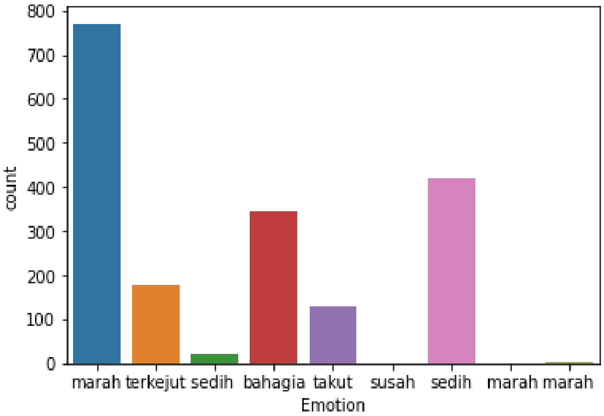

Figure 2. *Results of Emotions*

In this research experiment, we want to compare the oversampling method and the one without using the BERT method and the LSTM layer.

3.3. Data Preprocessing

At this phase, several stages are carried out: cleaning data from symbols and punctuation marks, then case-folding or changing words into lower sentences, then changing excess richness to less, for example, "Sayaaa" to "saya", clearing slang words, tokenizing: decapitating each word, then stopword removal or removes words that often appear. Finally, Stemming removes affixed words. The preprocessing results are shown in Table 3.

Table 3. *Data Preprocessing Results*

Comment	Preprocessing Results
Mana pak sampai detik ini gak ada bantuan untuk ojek online??	mana pak detik enggak bantu ojek online
Piye sih pak jokowi, bbm naik naiķ, pqdqhql itu artinya rakyat semakin menderita, karena harga2 barang lain pasti mèlonjak, rakyat semakin sulit cari uang, gaji/upah ajeg, rakyat Indonesia pasti tambah banyak yang miskin.	piye sih pak jokowi bbm naik nai pqdqhql arti rakyat makin derita harga barang lonjak rakyat makin sulit cari uang gaji upah ajeg rakyat indonesia tambah banyak miskin
Y Allah BBm naik Rakyak miskin pada Kelaparan..cari buat makan aja susah..	allah bbm naik rakyak miskin lapar cari buat makan susah
Kalo subsidi dinikmati ama orang yg mampu artinya pemerintah yg gak bisa ngatur 🤣	kalo subsidi nikmat sama orang mampu arti perintah enggak atur

Based on Table 3. The scraping result data is in the Comment column, and the preprocessing result is shown in the preprocessing result column.

3.4. Evaluation

The process is carried out to obtain good accuracy and facilitate computation. We can see the accuracy evaluation results of the oversampling process.

Table 4. *Accuracy Results of Train Data*

Dataset	Accuracy Result of Train Data
Without Oversampling	47%
Oversampling	95%

Based on Table 4. The highest result is obtained when oversampling gets 95% accuracy, while without oversampling, only 47%. Model evaluation is the final stage in the classification process intended to test the model that has been trained and tested. Model evaluation is carried out using new data that has been preprocessed and labeled. The evaluation results are shown in Figures 3 and 4.

	precision	recall	f1-score	support
0	0.00	0.00	0.00	29
1	0.38	0.90	0.54	138
2	0.18	0.06	0.08	90
3	0.60	0.16	0.25	77
4	0.00	0.00	0.00	39
accuracy			0.38	373
macro avg	0.23	0.22	0.17	373
weighted avg	0.31	0.38	0.27	373

Figure 3. *The Results Without Oversampling*

	precision	recall	f1-score	support
0	0.27	0.36	0.31	138
1	0.31	0.33	0.32	138
2	0.19	0.25	0.21	138
3	0.33	0.24	0.28	138
4	0.22	0.12	0.16	138
accuracy			0.26	690
macro avg	0.26	0.26	0.26	690
weighted avg	0.26	0.26	0.26	690

Figure 4. *The Results of Oversampling*

Based on the information provided in Figure 3, the test data exhibits an accuracy of 38%, indicating the presence of underfitting. Conversely, Figure 4 illustrates a test data accuracy of 28%, suggesting the occurrence of overfitting.

3.5. Discussion

The experiments shed light on the interplay between oversampling and the BERT method for emotion classification. Surprisingly, employing the oversampling technique alongside BERT yielded a decrease in accuracy during the testing phase, contrasting with the anticipated outcome. Notably, oversampling enhanced training accuracy, a common observation corroborated by prior studies. However, this seemingly beneficial approach can inadvertently exacerbate the phenomenon of overfitting, especially when the data distribution between classes is disparate. Overfitting manifests when the model becomes excessively attuned to the training data, capturing noise and quirks rather than underlying patterns. In severe class imbalances, oversampling exacerbates overfitting, leading to diminished generalization performance during testing. The inflated representation of minority classes through oversampling can skew the model's perception, impairing its ability to discern genuine patterns from noise.

Thus, while oversampling holds promise in addressing class imbalances and bolstering training accuracy, its indiscriminate application warrants caution. Contextual nuances, such as data distribution between classes, must be carefully considered to mitigate the risk of overfitting. Alternative strategies, such as synthetic data generation or algorithmic adjustments, may offer more nuanced solutions in scenarios characterized by substantial class disparities. Ultimately, striking a delicate balance between addressing class imbalances and mitigating overfitting remains pivotal in optimizing the performance and generalizability of emotion classification models. Further exploration and refinement of oversampling methodologies within the context of emotion classification are warranted to unlock its full potential while circumventing the pitfalls of overfitting.

4. CONCLUSION

In summary, this research addressed the surge of public discourse surrounding escalating fuel prices in Indonesia by leveraging advanced emotion classification techniques, specifically employing BERT and LSTM methods on YouTube data. The primary aim was to dissect and categorize the myriad emotions expressed by the populace in response to governmental decisions regarding fuel pricing. Remarkably, the study revealed that employing the oversampling technique yielded the highest accuracy of 95%, underscoring its efficacy in balancing class distribution and enhancing emotion classification accuracy. However, intriguingly, the amalgamation of oversampling with the BERT method unexpectedly resulted in reduced accuracy during testing, highlighting the nuanced interplay between different classification techniques.

In conclusion, this study illuminates the intricate landscape of public sentiment encapsulated within social media platforms, particularly in response to socio-economic upheavals such as fluctuations in fuel prices. Integrating BERT and LSTM methods alongside oversampling techniques provided invaluable insights into the efficacy and limitations of diverse emotion classification approaches. Notably, the substantial accuracy improvement facilitated by oversampling underscores its pivotal role in mitigating class imbalances within emotion classification datasets. Despite unforeseen accuracy dips in specific experiments, these findings enrich our comprehension of the complexities inherent in deciphering public emotions and reactions in the digital realm.

Future research endeavors will explore the integration of cutting-edge algorithms such as GPT and LLM, promising further advancements in emotion classification accuracy and insights derived from social media data. By continually refining and innovating methodologies, researchers can unlock the full potential of social media platforms as rich reservoirs of public sentiment and societal dynamics.

ACKNOWLEDGMENT

The authors would like to thank Amikom Purwokerto University for all the support that has been given and thank you to Gazi University Türkiye for giving us the opportunity.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

REFERENCES

[1] Danirmala, T., Nugroho, Y. S., "Analisis Sentimen Terhadap Topik Kenaikan Harga Bahan Bakar Minyak (BBM) pada Media Sosial Twitter", Indonesia Journal of Computer Science, 12(3), (2023).

[2] Wardani, W., Suriana, S., Arfah, S. U., Zulaili, Z., Lubis, P. S., "Dampak kenaikan Bahan Bakar Minyak (BBM) Terhadap Inflasi dan Implikasinya Terhadap Makroekonomi di Indonesia", All Fields of Science Journal Liaison Academia and Sosiety, 2: 63–70, (2022).

[3] Avvisa, A., Nuswardani, N., Darsono, D., "Tinjauan Yuridis Tentang Tanggung Jawab Hukum Terhadap Sewa Menyewa Tangki Minyak Antara PT Karyamas Niaga Manunggal Jaya Dengan Pertamina", Bachelor Thesis, Muhammadiyah Surakarta University, Surakarta, (2014).

[4] Silbaqolbina, Y. Z., Najicha, F. U., "Kebijakan Pemerintah Dalam Menaikkan Harga Bahan Bakar Minyak Serta Dampaknya Bagi Masyarakat", Jurnal Syntax Fusion, 2: 604–611, (2022).

[5] Sarbaini, S., Nazaruddin, N., "Pengaruh Kenaikan BBM Terhadap Laju Inflasi di Indonesia", Jurnal Teknologi dan Manajemen Industri Terapan, 2: 25–32, (2023).

[6] Satoto, E. B., “The Effect of Fuel Price Fluctuations, Exchange Rates, and Profitability on Stock Returns and Inflation as Intervening Variables”, Jurnal Ilmu Manajemen dan Bisnis, 8: 110-127, (2023).

[7] Dewi, Y., Saryono, S., Dini, A., Maghfiroh, M., Mauli, R., “Dampak Kenaikan Harga Bahan Bakar Minyak (BBM) Terhadap Sembilan Bahan Pokok (Sembako) Di Kecamatan Tambun Selatan Dalam Masa Pandemi”, Journal Citizenship Virtues, 2: 320-326, (2022).

[8] Mulyani, S., Novita, R., “Implementation of the Naive Bayes Classifier Algorithm for Classification of Community Sentiment About Depression on Youtube”, Jurnal Teknik Informatika, 3: 1355-1361, (2022).

[9] Saputra, F. H., Cholifah, C., “Pengaruh Narasi dalam Konten Vlog Channel Youtube ‘Menjadi Manusia’ Terhadap Sikap dalam Menjaga Kesehatan Mental”, Jurnal Ilmu Sosial dan Ilmu Politik, 19: 11-22, (2023).

[10] Ma’ruf, M., Kuncoro, A. P., Subarkah, P., Nida, F., “Sentiment analysis of customer satisfaction levels on smartphone products using Ensemble Learning”, Ilkom Jurnal Ilmiah, 14(3): 339-347, (2022).

[11] Nandwani, P., Verma, R., “A review on sentiment analysis and emotion detection from text”, Social Network Analysis and Mining, 11: 81, (2021).

[12] Mantello, P., Ho, M.-T., Nguyen, M.-H., Vuong, Q.-H., “Bosses without a heart: socio-demographic and cross-cultural determinants of attitude toward Emotional AI in the workplace”, AI and Society, 38: 97-119, (2023).

[13] Sapanji, R. A. E. V., Targa, T., Hamdani, D., Harahap, P., “Sentiment Analysis of the Top 5 E-commerce Platforms in Indonesia using Text Mining and Natural Language Processing (NLP)”, Journal of Applied Informatics and Computing, 7: 202-211, (2023).

[14] Sünnetci, K. M., Akben, S. B., Kara, M. M., Alkan, A., “Face mask detection using GoogLeNet CNN-Based SVM Classifiers”, Gazi University Journal of Science, 36: 645-658, (2023).

[15] Agrawal, S., Dutta, S., Patra, B. K., “Sentiment Analysis of Short Informal Text by Tuning BERT - Bi-LSTM Model”, IEEE EUROCON 2021 - 19th International Conference on Smart Technologies, 98-102, (2021).

[16] Wibowo, A. P., Darmawan, W., Amalia, N., “Komparasi Metode Naive Bayes dan K-Nearest Neighbor Terhadap Analisis Sentimen Pengguna Aplikasi PeduliLindungi”, IC-Tech Journal, 17: 18-23, (2022).

[17] Vashishtha, S., Gupta, V., Mittal, M., “Sentiment analysis using fuzzy logic: A comprehensive literature review”, WIREs Data Mining and Knowledge Discovery, 13: 64-101, (2023).

[18] Tombaloğlu, B., Erdem, H., “Turkish speech recognition techniques and applications of recurrent units (LSTM and GRU)”, Gazi University Journal of Science, 34: 1035-1049, (2021).

[19] Rahman, A. F., “Klasifikasi Tweet di Twitter dengan Menggunakan Metode K-Nearest Neighbor”, Jurnal Sistim Informatika dan Teknologi, 4: 64-69, (2022).

[20] Zhang, W., Li, L., Zhu, Y., Yu, P., Wen, J., “CNN-LSTM neural network model for fine-grained negative emotion computing in emergencies”, Alexandria Engineering Journal, 61: 6755-6767, (2022).

[21] Vimali, J. S., Murugan, S., “A Text Based Sentiment Analysis Model using Bi-directional LSTM Networks”, IEEE ICCES 2021 - 6th International Conference on Communication and Electronics Systems, 1652-1658, (2021).

[22] Negara, A. B. P., Muhardi, H., Sajid, F., “Perbandingan Algoritma Klasifikasi terhadap Emosi Tweet Berbahasa Indonesia”, Jurnal Edukasi dan Penelititian Informatika, 7: 242-249, (2021).

[23] Rahman, O. H., Abdillah, G., Komarudin, A., “Klasifikasi Ujaran Kebencian pada Media Sosial Twitter Menggunakan Support Vector Machine”, Jurnal Rekayasa Sistem dan Teknologi Informasi, 5: 17-23, (2021).

[24] Abri, R., Artuner, H., “LSTM-Based Deep Learning Methods for Prediction of Earthquakes Using Ionospheric Data”, Gazi University Journal of Science, 35: 1417-1431, (2022).

[25] Tyas, T. M. M., Purnamasari, A. I., “Penerapan Algoritma K-means dalam Mengelompokkan Demam Berdarah Dengue Berdasarkan Kabupaten”, Blend Sains Jurnal Teknik, 1: 277-283, (2023).

[26] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., Polosukhin, I., “Attention Is All You Need”, arXiv Preprint, Ithaca, (2023).

[27] Putra, I. M., Tahyudin, I., Rozaq, H. A. A., A. Syafa’at, Y., Wahyudi, R., Winarto, E., “Classification analysis of COVID19 patient data at government hospital of banyumas using machine learning”, IEEE ICSCEE 2021 - 2nd International Conference on Smart Computing and Electronic Enterprise: Ubiquitous, Adaptive, and Sustainable Computing Solutions for New Normal, 271-274, (2021).

[28] Tahyudin, I., Rozaq, H. A. A., Nambo, H., “Machine Learning Analysis for Temperature Classification using Bioelectric Potential of Plant”, IEEE ICITISEE 2022 - 6th International Conference on Information Technology, Information Systems and Electrical Engineering, 465-470, (2022).

[29] Elistiana, K. M., Kusuma, B. A., Subarkah, P., Rozaq, H. A. A., “Improvement of Naive Bayes Algorithm in Sentiment Analysis of Shopee Application Reviews on Google Play Store”, Jurnal Teknik Informatika, 4: 1431-1436, (2023).