Matrik: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer
Vol. 23, No. 1, November 2023, pp. 131∼142
ISSN: 2476-9843, accredited by Kemenristekdikti, Decree No: 200/M/KPT/2020
DOI: 10.30812/matrik.v23i1.3332

Analyzing Sentiment with Self-Organizing Map and Long Short-Term Memory Algorithms

Frans Mikael Sinaga , Sio Jurnalis Pipin, Sunaryo Winardi , Karina Mannita Tarigan , Ananda Putra Brahmana
Universitas Mikroskil, Medan, Indonesia

Article Info

Article history:

Received August 29, 2023
Revised 31 October, 2023
Accepted 15 November, 2023

Keywords:

Long Short-Term Memory
Memory Algoritms
Self-Organizing Map
Sentiment Analysis

ABSTRACT

This research delves into the impact of Chat Generative Pre-trained Transformer, one of Open Artificial Intelligence Generative Pretrained Transformer models. This model underwent extensive training on a vast corpus of internet text to gain insights into the mechanics of human language and its role in forming phrases, sentences, and paragraphs. The urgency of this inquiry arises from Chat Generative Pre-trained Transformer emergence, which has stirred significant debate and captured widespread attention in both research and educational circles. Since its debut in November 2022, Chat Generative Pre-trained Transformer has demonstrated substantial potential across numerous domains. However, concerns voiced on Twitter have centered on potential negative consequences, such as increased forgery and misinformation. Consequently, understanding public sentiment toward Chat Generative Pre-trained Transformer technology through sentiment analysis has become crucial. The research's primary objective is to conduct Sentiment Analysis Classification of Chat Generative Pre-trained Transformer regarding public opinions on Twitter in Indonesia. This goal involves quantifying and categorizing public sentiment from Twitter's vast data pool into three clusters: positive, negative, or neutral. In the data clustering stage, the Self-Organizing Map technique is used. After the text data has been weighted and clustered, the next step involves using the classification technique with Long Short-Term Memory to determine the public sentiment outcomes resulting from the presence of Chat Generative Pre-trained Transformer technology. Rigorous testing has demonstrated the robust performance of the model, with optimal parameters: relu activation function, som_size of 5, num_epoch_som and num_epoch_lstm both at 128, yielding an impressive 95.07% accuracy rate.

Corresponding Author:

Frans Mikael Sinaga, +6282248148374,
Faculty of Informatics and Undergraduate Program of Computer Science,
Universitas Mikroskil, Medan, Indonesia,
Email: frans.sinaga@mikroskil.ac.id

How to Cite:
Author, "Analyzing Sentiment with Self-Organizing Map and Long Short-Term Memory Algorithms", *MATRIK: Jurnal Managemen,Teknik Informatika, dan Rekayasa Komputer*, Vol. 23, No. 1, pp. xxx-xxx, Nov, 2023.

1. INTRODUCTION

The progression of Natural Language Processing (NLP) technology has led to numerous advancements that have left a profound impact on diverse facets of our existence. One notable example is ChatGPT, an NLP model that has gained increasing popularity and utility across various industries worldwide, including in Indonesia. NLP models like ChatGPT play a crucial role in processing and understanding public sentiment, conducting consumer analysis, and even modeling human-computer interactions [1]. Furthermore, the presence of ChatGPT has also made its way into the realm of business, such as content writing and copywriting. The use of ChatGPT enables the selection of appropriate topics and writing styles, with outcomes characterized by minimal plagiarism [**?**]. The utilization of Generative Pre-Training (GPT) technology has also proven to enhance natural language understanding [2], indicating the potential of models like GPT to learn from limited examples [3]. Considering the current landscape, ChatGPT has evolved into a pre-trained language model that generates increasingly sophisticated conversation responses [4]. It can even support the development of more advanced chatbots [5].

Nevertheless, similar to any technological progress, the utilization of ChatGPT also raises concerns that demand thoughtful analysis, especially within the realm of education. The consequences of ChatGPT's application in an educational setting require substantial scrutiny. Overdependence on this technology may, in theory, diminish the capacity for critical thinking and independent problem-solving among both learners and instructors. Collaborative Learning Theory supports the view that technology use, such as ChatGPT, can create opportunities for collaborative learning where students interact with both technology and their peers to enhance their understanding. Furthermore, the potential for students to use ChatGPT for cheating in assignments and exams poses a threat to academic integrity and blurs the boundaries of clear grading standards. The use of this technology can also lead to student disengagement in learning specific skills and knowledge, as they may come to rely on ChatGPT as their primary source of answers. The Self-Directed Learning Theory explains how the use of such technology may hinder self-directed learning and the ability of students to independently solve problems. Moreover, it's not always the case that ChatGPT provides accurate or adequate answers, especially in complex educational contexts, which can ultimately affect the overall quality of education [6]. Therefore, in addition to the significant benefits, there are also concerns that need to be considered in the use of ChatGPT. Ethical and regulatory issues have become increasingly relevant as the use of this technology grows. Thorough research is needed concerning the resilience, interpretation, and ethical aspects of ChatGPT usage [7]. The Theory of Ethics of Technology can assist in identifying potential ethical issues that may arise and provide guidelines for the use of this technology.

In this particular context, the present study seeks to evaluate user sentiment following their interactions with ChatGPT. By examining public sentiments expressed on the social media platform Twitter, particularly within the domains of research and education, this research will employ datasets containing user feedback to acquire more profound insights. The methodology employed will encompass text analysis utilizing the Term Frequency-Inverse Document Frequency (TF-IDF) technique [8, 9], Performing text grouping through the application of the Self-Organizing Map (SOM) technique [10], Conducting multiclass sentiment analysis using the Long Short-Term Memory (LSTM) approach [11]. During the concluding phases of the study, the model's performance will be assessed by employing a confusion matrix to gauge the precision of sentiment analysis outcomes [12]. This holistic strategy will offer clarity on user perceptions and reactions to engagements with ChatGPT, specifically within the spheres of research and education, and offer valuable perspectives regarding the ramifications and potential advantages of this technology.

When exploring the consequences of technologies such as ChatGPT, the Social Adjustment Theory offers intriguing insights. This theory delineates how both individuals and societies undergo a gradual adaptation process in response to technological shifts. The introduction of ChatGPT not only reshapes the landscape of business and education but also impacts the manner in which individuals engage with their surroundings, encompassing their expression of opinions, communication methods, and learning approaches [5].

The Social Constructivism Theory provides a valuable perspective for understanding human interaction with technology. According to this theory, knowledge and understanding are not solely shaped by individuals but also by their interactions with the environment and others [**?**]. The utilization of ChatGPT and analogous technologies embodies a novel mode of interaction capable of molding the collective comprehension of language, communication, and social environments. Within this broad conceptual framework, our research endeavors to assess user sentiment following interactions with ChatGPT. By examining public sentiments expressed on the social media platform Twitter, particularly within the domains of research and education, this study will employ datasets containing user feedback to acquire more profound insights. The research approach will encompass text weighting through the utilization of the Term Frequency-Inverse Document Frequency (TF-IDF) technique [8, 9], Performing text grouping via the application of the Self-Organizing Map (SOM) methodology [6], Additionally, conducting multiclass sentiment analysis utilizing the Long Short-Term Memory (LSTM) approach [6].

The distinction in this research from previous research stages lies in the inclusion of a clustering process. The following are the stages in the SOM method. In the concluding phases of our study, we will evaluate the model's performance by employing a confusion matrix to gauge the precision of sentiment analysis results. This holistic approach strives to offer deeper insights into how users perceive and react to interactions with ChatGPT, especially within research and educational contexts. Furthermore, it aims to shed light on how technological interactions contribute to the collaborative construction of knowledge and understanding in the digital era [13].

2. RESEARCH METHOD

This research is underpinned by a robust framework encompassing multiple stages: data preprocessing, text data weighting, and the assignment of labels to the weighted text data. These labels align with sentiment analysis theory, encompassing positive, negative, and neutral categories. Following this, the weighted data undergoes clustering, succeeded by the application of classification techniques to derive public sentiment insights concerning ChatGPT usage. Figure 1 illustrates the stages of the Problem-Solving Approach employed in this study.

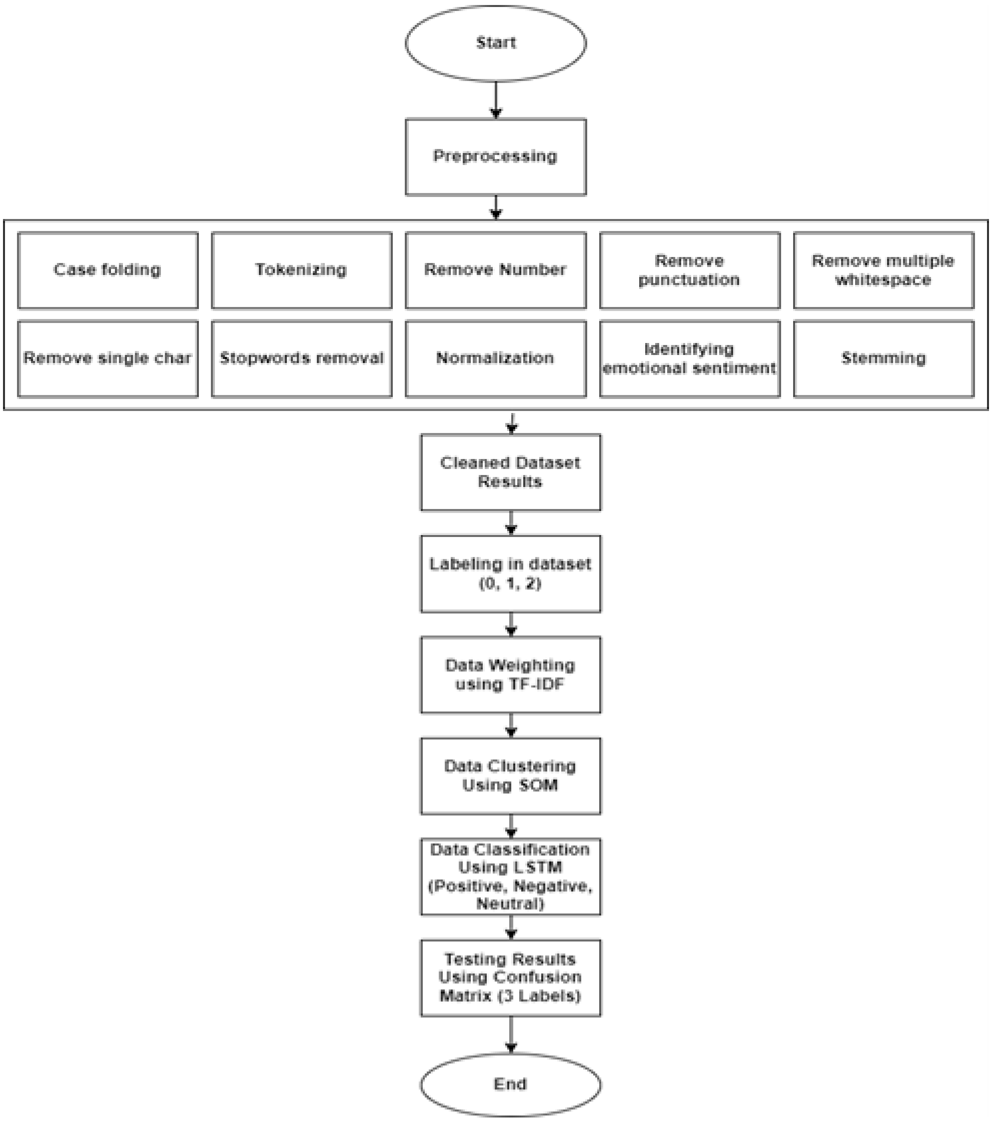

Figure 1. The steps in problem solving approach

2.1. Data preparation

Data Preparation This stage involves data crawling or web scraping. For data crawling, software tools known as ”crawlers” or ”spiders” are commonly employed. Here are the Twitter dataset keywords used in this research from November 2022 to 2023, ChatGPT, OpenAI, Education, Research.

2.2. Pre-processing data

This process consists of case folding, tokenizing, white space removal, number removal, punctuation removal, removal of multiple white spaces, removal of single characters, and stopwords removal using an Indonesian stopwords dataset for filtering, which involves selecting important words from the tokenized output. Normalization is performed using the slang-indonesia-lexicong dataset to convert slang words into standard words based on the Indonesian Dictionary (KBBI). Figure 2 displayed here is an example of the cleaned text data from Twitter.

URL	Date	Tweet	ID	Replies	Retweets	Likes	Quotes	Conv. ID	Language	Links	Media	Retweetec	Bookmark	Username	Label
https://tw	2023-06-2	semua itu ðŸ'€	1.67E+18	1	0	0	0	1.67E+18	in				0	wajahmen	Negatif
https://tw	2023-06-2	OpenAI berupaya secara aktif	1.67E+18	0	0	0	0	1.67E+18	in	https://dailysocial.id/post/kunju			0	dailysocial	Positif
https://tw	2023-06-2	Kontol, semuanya kontol. Na	1.67E+18	0	0	2	0	1.67E+18	in	http://c.ai			0	yoo_oojin	Negatif
https://tw	2023-06-2	anjeng bangun" dikasih kaba	1.67E+18	1	1	0	0	1.67E+18	in				0	nailavonga	Negatif
https://tw	2023-06-2	Ni kalo kena banned openai k	1.67E+18	0	0	0	0	1.67E+18	in				0	yochengzu	Netral
https://tw	2023-06-2	Hdh, pdal gue sdh ganbatte n	1.67E+18	0	0	0	0	1.67E+18	in				0	kuzushiyaa	Negatif
https://tw	2023-06-2	waduh gue dibanned lagi san	1.67E+18	0	0	0	0	1.67E+18	in				0	Miegumiw	Negatif
https://tw	2023-06-2	Lets see ini acc openai bertah	1.67E+18	0	0	0	0	1.67E+18	in				0	mkzeai	Netral
https://tw	2023-06-2	https://t.co/ZuVRqHJS4u	1.67E+18	0	1	3	0	1.67E+18	in	https://www.siasat.com/deepm			1	khademin	Netral
https://tw	2023-06-2	JUST IN: Pengguna melapork	1.67E+18	0	0	1	0	1.67E+18	in				0	Coingraph	Negatif
https://tw	2023-06-2	https://t.co/yprMfnesBa	1.67E+18	1	0	3	0	1.67E+18	in	https://www.kompas.id/baca/in			0	hariankom	Netral
https://tw	2023-06-2	@kaeniiya openai is killing m	1.67E+18	1	0	1	0	1.67E+18	in				0	jingyuuan	Negatif
https://tw	2023-06-2	https://t.co/VdU9zBjEow	1.67E+18	0	0	0	1	1.67E+18	in	https://bit.ly/3NomWGQ			0	kukuhtw	Netral
https://tw	2023-06-2	#Kompas58 #menjadilebih	1.67E+18	1	0	1	0	1.67E+18	in				0	hariankom	Netral
https://tw	2023-06-2	https://t.co/0yQy5ECkTn	1.67E+18	0	0	0	0	1.67E+18	in	https://www.bloombergtechno			0	Bloomberg	Positif
https://tw	2023-06-2	https://t.co/M8q1dvp8E3	1.67E+18	0	1	2	0	1.67E+18	in	https://channel9.id/sleekflow-te			0	IdChannel	Positif
https://tw	2023-06-2	@osaeragi @babufess pake j	1.67E+18	1	0	1	0	1.67E+18	in				0	gfepard	Netral

Figure 2. Example of pre-processed tweet results

Following the completion of the data preprocessing phase, the subsequent stage involves data weighting, employing the Term Frequency-Inverse Document Frequency (TF-IDF) method as described in Equation (1).

$$TF - IDF = \frac{\text{Ter Frequency}}{\text{Document Frequency}} \tag{1}$$

2.3. Cluster data

In this research, the difference compared to the previous stage [14] lies in the addition of a data clustering step before the weighting and classification process. The steps in the Self-Organizing Map (SOM) method [10] encompass the initialization of the SOM grid with random weights for each neuron, the computation of distances between data to determine the Best Matching Unit (BMU) following Equation (2), the adjustment of the BMU's weights and those of its neighboring neurons within the SOM grid using Equation (3), and the iterative weight updates in accordance with Equation (4). This procedure is reiterated for a predefined number of iterations or until convergence is attained.

1. Intialization
2. Best Matching Unit (BMU)

$$d_{ij}\sqrt{\Sigma_{k=1}^{n}(X_{ki} - X_{kj})^2} \tag{2}$$

Where:
d_{ij} : The separation or distance between instance i and j
X_{ki} : Two distinct instances, labeled as i and j

3. Weight Update Formula

$$\sigma(t) = \sigma_0 exp(-\frac{t}{n}.t) = 1, 2, 3, \ldots \tag{3}$$

where
$\sigma(t)$: radius at time t_0
t : current time step = 1. 2. 3
π : current time
The update formula for neurons is given by:

$$Wi' = W2 + \sigma(t)Wi(Xi - Wi) \tag{4}$$

Where :
Wi : weight
Xi : neuron

4. Iteration: This process is repeated until clusters are formed.

2.4. Data classification

The categorization of data into three classes, specifically positive (acceptance), negative (rejection), and neutral, follows a series of procedures grounded in the LSTM method [15]. These procedures encompass identifying the information to be forgotten or removed from the cell state as per Equation (5), determining the new information to be stored in the cell state using Equation (6), and calculating the candidate value for the new cell state through the activation of the tanh function applied to the combination of the prior output and the current input, following Equation (7). Subsequently, the previous cell state is updated with the new cell state, guided by Equation (8), and the output is derived from the cell state as outlined in using Equation (9). The ultimate output is computed by multiplying Ot with the tanh value of the current cell state.

1. Identifying the data to be eliminated or forgotten from the cell state.

$$ft = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{5}$$

2. Identifying the fresh data to be preserved in the cell state.

$$it = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{6}$$

$$\hat{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{7}$$

3. Transitioning the prior cell state (Ct1) to the current cell state (Ct).

$$C_t = ft * C_{t-1} + it * \hat{C}_t \tag{8}$$

4. Outcome derived from the cell state

$$\begin{gathered} O_t = \sigma(W_o[h_{t-1}, x_t]) + b_0 \\ h_t = o_t * tanh(C_t) \end{gathered} \tag{9}$$

2.5. Data testing

To assess the model's performance, we can utilize a confusion matrix, a valuable tool for calculating the system's accuracy. The confusion matrix serves as a key performance metric and comprises four terms to delineate the outcomes of the classification process: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). True Negative (TN) denotes the correct identification of negative data, while False Positive (FP) represents the misclassification of negative data as positive. True Positive (TP) signifies the accurate classification of positive data, whereas False Negative (FN) indicates the erroneous classification of positive data as negative.

At this stage, an assessment is carried out for the employed classification technique. This study employs accuracy testing as a means to evaluate the classification method's performance, as outlined in Equation (10).

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)) * 100\% \tag{10}$$

3. RESULT AND ANALYSIS

Here are the results of this research, which include the Twitter Data Crawling results, followed by data preprocessing outcomes, then data weighting results, data clustering, and data classification to observe public sentiment towards the presence of ChatGPT. Subsequently, testing was conducted on cluster parameters to assess the impact of classification results under different cluster parameters. Testing was also carried out on the classification stages.

3.1. The results of crawling the dataset

Presented below are the findings obtained through the extraction of text data from Indonesian Twitter. This dataset covers the time frame between January 2022 and June 2023, resulting in a collection of 5000 entries gathered through the utilization of a variety of keywords. The results of this data extraction from Twitter are displayed in Table 1.

Table 1. The Crawled Dataset Results

URL	Date	Tweet	ID	Replies	Retweet	Likes	Quotes
https://twitter.com/AkademiaRnD/status/1659382137005703171	2023-05-19 02:15:05+00:00	Aduhhh baru nak puji ke-artistic-an dia tetiba chatgpt $\eth\ddot{Y}\ -\eth\ddot{Y}'''a$	1.67E+18	0	0	1	0
https://twitter.com/PatronGaeul/status/1674405840919609347	2023-06-29 13:13:56+00:00	Chatgpt sekarang bisa typing jamet jg yah	1.67E+18	0	1	0	0
https://twitter.com/agstt/status/1674366844415934464	2023-06-29 10:38:58+00:00	Sepertinya sekarang istilah ”mbah google” tahtanya sudah bisa digantikan oleh ”mbah chatGPT”	1.67E+18	1	3	18	0
https://twitter.com/erhanazrai/status/1674227890920259586	2023-06-29 01:26:49+00:00	Kotak tengah cari talent yg ada 10 tahun experience in chatgpt.	1.67E+18	8	2	13	1
https://twitter.com/Lahilapagi/status/1672594575935041537	2023-06-24 13:16:36+00:00	@kafirmasi Ni nder penjelasannya. Source: OpenAi https://t.co/jyWdw394KO	1.67E+18	3	135	1020	12
https://twitter.com/chanW0NY/status/1673420220978049025	2023-06-26 19:57:25+00:00	chatgpt juga nyerah jawabnya	1.67E+18	0	0	0	0

3.2. The results of labeling the dataset

Sentiment analysis was conducted on the public sentiments expressed by Twitter users within the obtained dataset. The analysis categorizes sentiments into three classes, corresponding to positive, negative, and neutral, in alignment with sentiment analysis theory. These sentiment analysis results are then applied as labels to the dataset. The labeled dataset outcomes are presented in in Table 2.

Table 2. The Results of Labeling the Dataset

Label	Tweet	Date	Username	Jury 1	Jury 2	Jury 3
Netral	Aduhhh baru nak puji ke-artistic-an dia tetiba chatgpt $\eth\ddot{Y}\ -\eth\ddot{Y}'''a$	2023-05-19 02:15:05+00:00	AkademiaRnD	Positif	Netral	Netral
Negatif	Chatgpt sekarang bisa typing jamet jg yah	2023-06-29 13:13:56+00:00	PatronGaeul	Negatif	Negatif	Netral
Positif	Sepertinya sekarang istilah ”mbah google” tahtanya sudah bisa digantikan oleh ”mbah chatGPT”	2023-06-29 10:38:58+00:00	agstt	Positif	Positif	Positif
Netral	Kotak tengah cari talent yg ada 10 tahun experience in chatgpt.	2023-06-29 01:26:49+00:00	erhanazra	Netral	Netral	Netral
Positif	@kafirmasi Ni nder penjelasannya. Source: OpenAi https://t.co/jyWdw394KO	2023-06-24 13:16:36+00:00	Lahilapagi	Positif	Positif	Netral
Negatif	chatgpt juga nyerah jawabnya	2023-06-26 19:57:25+00:00	ChanW0NY	Negatif	Negatif	Negatif

3.3. The results of data preprocessing

The data collected through Twitter crawling undergoes a series of preprocessing steps, which encompass Case Folding, Tokenization, Number Removal, Punctuation Removal, Elimination of Multiple Whitespaces, Single Character Removal, Stopwords Removal, Normalization, and Stemming. Presented below are the outcomes of the data preprocessing.

1. Outcomes of Case Folding
   Case folding entails the conversion of all text characters into lowercase letters. The outcomes of this case folding process are displayed in Table 3.

Table 3. Case Folding Results

Case Folding Results	
Before case folding text	After case folding text
ChatGPT error ya . . . lagi mau nugas	chatgpt error ya . . . lagi mau nugas

2. Tokenizing results
   Tokenization involves dividing text into smaller units referred to as 'tokens.' The outcomes of this tokenization process are illustrated in Table 4.

Table 4. Tokenizing Results

Tokenizing Results	
Before tokenizing text	After tokenizing text
berteman dengan chatgpt	['berteman', 'dengan', 'chatgpt']

3. Token frequency results
   Token frequency represents the tally of occurrences of a given word or token within a text or language corpus. In this context, it pertains to individual words, phrases, or symbols in a specific language. The outcomes of token frequency analysis are presented in Table 5.

Table 5. Token Frequency Results

Tokenizing results	Token frequency results
['berteman', 'dengan', 'chatgpt']	<FreqDist with 3 samples and 3 outcomes>

4. Stopwords removal results
   Eliminating stopwords can assist in focusing the analysis on words of greater relevance and significance within the given context. The outcomes of the stopwords removal process are available in Table 6.

Table 6. Stopwords Removal Results

Stopwords Removal Results		
Text data	Tokenizing	Stopwords removal
Berteman dengan chatgpt	['berteman', 'dengan', 'chatgpt']	['berteman', 'chatgpt']

3.4. The results of text data weighting

Text Data Weighting involves the application of the Term Frequency-Inverse Document Frequency (TF-IDF) technique, which assigns weights to individual words within the text. The outcomes of the text data weighting process are presented in Table 7.

1. Encoded label results

Table 7. Encoded Label Results

Encoded_Labels	aa	aalona	ababe	abang	abap	abc	abda
1	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0.332403
1	0	0	0	0	0	0	0
0	0	0	0	0.157007	0	0	0
2	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
2	0.272384	0	0	0	0	0	0
1	0	0	0	0	0	0	0.332288

2. Data normalization results
   Data normalization is applied to the previously weighted text data, and this step is executed to standardize the data range values prior to conducting clustering and classification processes. The outcomes of data normalization are displayed in Table 8.

Table 8. Data Normalization Results

zilis	zinazofanya	zoom	zuckerberg	zuidema	Encoded_Labels
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	1
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	1
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	1
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	0
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	2
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	2
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	2
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	2
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	1
-0.023100172	-0.023100172	-0.039737156	-0.023100172	-0.032677296	2

3.5. The results of SOM + LSTM

Presented below are the test results stemming from the utilization of the Self-Organizing Map (SOM) and LSTM models. This section showcases the outcomes of the conducted tests, encompassing parameter experimentation for clustering in the SOM model and activation function assessment in the LSTM model. The purpose of these tests is to compare the performance of each model under various parameter settings. Table 9 illustrates that the ReLU activation function yields the highest accuracy of 95.07%. Additionally, Table 10 demonstrates that the sigmoid activation function results in the highest accuracy of 82.01%, while Table 11, indicates that the softmax activation function leads to the highest accuracy of 82.91%. It's important to note that these presented test results do not preclude the possibility of achieving superior performance through further experimentation with different parameters and a larger dataset, allowing for a more comprehensive assessment of model performance.

Table 9. The ReLU Activation Function

The ReLU activation function							
No.	Som_Size	Sigma	Learning_rate	num_epoch_som	num_epoch_LSTM	batch_size	Akurasi
1	5	0.5	0.01	100	128	32	90.69%
2	5	0.8	0.08	100	128	32	95.01%
3	5	1,0	0.001	100	128	32	95.07%

Table 10. The Sigmoid Activation Function

The sigmoid activation function							
No	**Som_Size**	**Sigma**	**Learning_rate**	**num_epoch_som**	**num_epoch_LSTM**	**batch_size**	**Akurasi**
1	5	0.5	0.01	100	128	32	79.02%
2	5	0.8	0.08	100	128	32	80.09%
3	5	1,0	0.001	100	128	32	82.01%

Table 11. The Softmax Activation Function

The softmax activation function							
No	Som_Size	Sigma	Learning_rate	num_epoch_som	num_epoch_LSTM	batch_size	Akurasi
1	5	0.5	0.01	100	128	32	81.80%
2	5	0.8	0.08	100	128	32	81.01%
3	5	1,0	0.001	100	128	32	82.91%

3.6. Analysis and Discussion

Based on the literature review conducted, several models have been identified and utilized for the purpose of categorizing public sentiment towards various subjects, including technologies like ChatGPT and government policies. Previous research has predominantly employed supervised models such as the Nave Bayes Classifier, SVM, K-Nearest Neighbor, and DecisionTree [16, 17], However, the integration of supervised and unsupervised learning models has not been explored extensively in prior studies. Consequently, in this research, we introduce a clustering technique as a preprocessing step before data classification. The objective of incorporating these models is to enhance the overall performance of the classification model. By initially clustering the data to reduce the distance between data points, the subsequent application of the classification model yields improved results and facilitates more consistent outcomes [4].

In this study, a series of stages are employed in the data preprocessing phase. This includes processes like Case Folding, Tokenization, whitespace management, number removal, punctuation elimination, double space removal, single character deletion, and stopwords removal, utilizing an Indonesian language stopwords dataset for filtration. The objective is to select essential terms from the tokenized results. Additionally, we conduct normalization using the 'slang-indonesia-lexicon' dataset to standardize slang words to their corresponding entries in the KBBI (Indonesian Standard Dictionary). Before clustering the data, it is crucial to weigh the text using the Term Frequency-Inverse Document Frequency (TF-IDF) technique [9]. The weighted data simplifies clustering using the SOM Clustering model. Subsequently, data classification is performed with the LSTM model to determine public sentiment classification concerning the presence of ChatGPT. We have conducted testing on the applied models, including clustering testing on the SOM Clustering model. Furthermore, we conducted tests on the LSTM model by comparing different activation function parameters within it to evaluate their influence on accuracy. The test results are detailed in tables 9, 10 and 11. During testing, we applied various activation functions and observed that the ReLU activation function consistently yielded superior accuracy rates.

4. CONCLUSION

The conclusion of this research is that the applied model is capable of classifying public sentiment towards ChatGPT technology. This model can classify sentiments into three labels: Positive, Neutral, and Negative. The implementation of clustering techniques using Self-Organizing Map (SOM) in this study has proven to be effective in achieving better classification results, especially with a cluster parameter of 5. The use of data weighting techniques with the TF-IDF method has also been shown to improve SOM's performance during data grouping. Our recommendation is to conduct experiments with different parameters for each model to find the most suitable parameters for higher accuracy. Additionally, it is important to incorporate the Silhouette Coefficient model in the clustering phase to obtain optimal clusters before classifying the data.

5. ACKNOWLEDGEMENTS

We express our sincere appreciation to the Directorate of Research, Technology, and Community Service (DRTPM) under the Ministry of Research, Technology, and Higher Education of Indonesia for their generous financial support via the Community Research and Service Program grant for the fiscal year 2023. This support has been instrumental in enabling us to delve deeper into the dynamics of public opinion surrounding the ChatGPT phenomenon in Indonesia.

6. DECLARATIONS

AUTHOR CONTIBUTION

All authors have made significant contributions to the design, implementation, data analysis, and manuscript writing of this study. The individual contributions of each author are outlined as follows: Frans Mikael Sinaga: Analyzing issues, selecting appropriate models for problem-solving, cleaning datasets, clustering data, testing outcomes, and writing the research paper. Sio Jurnalis Pipin: Implementing data preprocessing techniques and applying data classification techniques. Sunaryo Winardi: Labeling datasets and weighting text data. Karina Mannita Tarigan: Crawling text data from Twitter Indonesia. Ananda Putra Brahmana: Crawling text data from Twitter Indonesia.

FUNDING STATEMENT

This research is supported by DRTPM - Directorate General of Higher Education, Ministry of Education and Culture of the Republic of Indonesia, with Contract Number 022/UM.348/LP/08/PN/2023. The authors would like to state that this funding has no influence on the research design, data collection and interpretation, manuscript preparation, or the decision to publish.

COMPETING INTEREST

The authors declare that there are no competing interests that could affect the results or interpretation of this manuscript. There are no financial relationships or personal interests that could create potential conflicts of interest.

REFERENCES

[1] B. D. Lund, T. Wang, N. R. Mannuru, B. Nie, S. Shimray, and Z. Wang, "ChatGPT and a new academic reality: Artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing," *Journal of the Association for Information Science and Technology*, vol. 74, no. 5, pp. 570–581, may 2023. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/asi.24750https://onlinelibrary.wiley.com/doi/abs/10.1002/asi.24750https://asistdl.onlinelibrary.wiley.com/doi/10.1002/asi.24750

[2] N. Shi, Q. Zeng, and R. Lee, "Language Chatbot-The Design and Implementation of English Language Transfer Learning Agent Apps," *2020 IEEE 3rd International Conference on Automation, Electronics and Electrical Engineering, AUTEEE 2020*, pp. 403–407, nov 2020.

[3] J. Kleesiek, Y. Wu, G. Stiglic, J. Egger, and J. Bian, "An Opinion on ChatGPT in Health CareWritten by Humans Only," *Journal of Nuclear Medicine*, vol. 64, no. 5, pp. 701–703, apr 2023. [Online]. Available: https://jnm.snmjournals.org/content/early/2023/04/13/jnumed.123.265687https://jnm.snmjournals.org/content/early/2023/04/13/jnumed.123.265687.abstract

[4] A. Faesal, A. Muslim, A. H. Ruger, and K. Kusrini, "Sentimen Analisis pada Data Tweet Pengguna Twitter Terhadap Produk Penjualan Toko Online Menggunakan Metode K-Means," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 19, no. 2, pp. 207–213, may 2020. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/640

[5] I. Dergaa, K. Chamari, P. Zmijewski, and H. B. Saad, "From human writing to artificial intelligence generated text: examining the prospects and potential threats of ChatGPT in academic writing," *Biology of Sport*, vol. 40, no. 2, pp. 615–622, 2023. [Online]. Available: https://doi.org/10.5114/biolsport.2023.125623

[6] Y. Akbar and T. Sugiharto, "Analisis Sentimen Pengguna Twitter di Indonesia Terhadap ChatGPT Menggunakan Algoritma C4.5 dan Naïve Bayes (Yuma Akbar 1*, Tri Sugiharto 2) Analisis Sentimen Pengguna Twitter di Indonesia Terhadap ChatGPT Menggunakan Algoritma C4.5 dan Naïve Bayes," *Jurnal Sains dan Teknologi*, vol. 5, no. 1, pp. 115–122, 2023. [Online]. Available: https://doi.org/10.55338/saintek.v4i3.1368

[7] M. Farrokhnia, S. K. Banihashem, O. Noroozi, and A. Wals, "A SWOT analysis of ChatGPT: Implications for educational practice and research," *Innovations in Education and Teaching International*, apr 2023. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/14703297.2023.2195846

[8] N. N. Amir Sjarif, N. F. Mohd Azmi, S. Chuprat, H. M. Sarkan, Y. Yahya, and S. M. Sam, "SMS Spam Message Detection using Term Frequency-Inverse Document Frequency and Random Forest Algorithm," *Procedia Computer Science*, vol. 161, pp. 509–515, jan 2019.

[9] A. Patil, "Word Significance Analysis in Documents for Information Retrieval by LSA and TF-IDF using Kubeflow," *Lecture Notes in Networks and Systems*, vol. 209, pp. 335–348, 2022. [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-16-2126-0{_}29

[10] F. Mikael Sinaga, P. Sirait, and A. Halim, "Optimization of SV-kNNC using Silhouette Coefficient and LMKNN for Stock Price Prediction," *2020 3rd International Seminar on Research of Information Technology and Intelligent Systems, ISRITI 2020*, pp. 326–331, dec 2020.

[11] D. I. Af'idah, D. Dairoh, S. F. Handayani, R. W. Pratiwi, and S. I. Sari, "Sentimen Ulasan Destinasi Wisata Pulau Bali Menggunakan Bidirectional Long Short Term Memory," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 21, no. 3, pp. 607–618, jul 2022. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/1402

[12] F. D. Ananda and Y. Pristyanto, "Analisis Sentimen Pengguna Twitter Terhadap Layanan Internet Provider Menggunakan Algoritma Support Vector Machine," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 20, no. 2, pp. 407–416, may 2021. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/1130

[13] P. T. Putra, A. Anggrawan, and H. Hairani, "Comparison of Machine Learning Methods for Classifying User Satisfaction Opinions of the PeduliLindungi Application," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 22, no. 3, pp. 431–442, jun 2023. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/2860

[14] W. Riyadi and J. Jasmir, "Performance Prediction of Airport Traffic Using LSTM and CNN-LSTM Models," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 22, no. 3, pp. 627–638, jul 2023. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/3032

[15] V. Raveendirarasa and C. R. Amalraj, "Sentiment Analysis of Tamil-English Code-Switched Text on Social Media Using Sub-Word Level LSTM," *Proceedings of ICITR 2020 - 5th International Conference on Information Technology Research: Towards the New Digital Enlightenment*, dec 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9310817

[16] M. K. Anam, B. N. Pikir, M. B. Firdaus, S. Erlinda, and A. Agustin, "Penerapan Naïve Bayes Classifier, K-Nearest Neighbor (KNN) dan Decision Tree untuk Menganalisis Sentimen pada Interaksi Netizen dan Pemeritah," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 21, no. 1, pp. 139–150, nov 2021. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/1092

[17] A. J. Makrufi, W. Fawwaz, and A. Maki, "Support vector machine with a firefly optimization algorithm for classification of apple fruit disease," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 22, no. 1, pp. 177–188, nov 2022. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/matrik/article/view/2365

[This page intentionally left blank.]