SENTIMENT ANALYSIS USING CONVOLUTIONAL NEURAL NETWORK (CNN) AND PARTICLE SWARM OPTIMIZATION ON TWITTER

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Abstract*—Over time, social media has always changed quickly. People can voice their ideas on various topics and communicate with each other through social media. One social media platform that allows users to express their ideas through tweets is Twitter. Sentiment is the route via which each person can express their ideas on a variety of subjects. The sentiment can be positive or negative. Sentiment analysis can be used to determine how Twitter users feel about particular subjects. Sentiment analysis on popular subjects in 2023, specifically the 2024 presidential contenders, will be done in this research. The dataset used in this research consists of 37,391 entries with 5 keywords. The research aims to understand how Twitter users respond and express their sentiments towards the presidential candidate through the use of deep learning classification techniques with Convolutional Neural Network (CNN), feature extraction using Term Frequency-Inverse Document Frequency (TF-IDF) method, and feature expansion with Word2Vec. Furthermore, this study employs Particle Swarm Optimization as an optimization technique to enhance the sentiment analysis model's performance. The test's results demonstrate a high degree of accuracy, offering a comprehensive picture of Twitter users' sentiments and perspectives toward the 2024 presidential contenders. This research helps to understand the dynamics of public opinion in the political context. Based on the evaluation results of the research, it yielded an accuracy of 78.2%, showcasing an improvement of 10.07% compared to the baseline.*

Keywords*: CNN, Particle Swarm Optimization, sentiment, TF-IDF, Word2vec.*

Intisari—*Seiring berjalannya waktu, media sosial selalu berubah dengan cepat. Orang-orang dapat menyuarakan ide-ide mereka tentang berbagai topik dan berkomunikasi satu sama lain melalui media sosial. Salah satu platform media sosial yang memungkinkan pengguna untuk mengekspresikan ide mereka melalui tweet adalah Twitter. Sentimen adalah jalur di mana setiap orang dapat mengekspresikan ide-ide mereka tentang berbagai hal. Sentimen tersebut dapat bernilai positif maupun negatif. Analisis sentimen dapat digunakan untuk menentukan bagaimana perasaan pengguna Twitter terhadap suatu topik tertentu. Analisis sentimen pada subjek populer pada tahun 2023, khususnya calon presiden 2024. Dataset yang digunakan pada penelitian ini berjumlah 37,391 dengan 5 keyword. Penelitian ini bertujuan untuk memahami bagaimana pengguna Twitter merespon dan mengekspresikan sentimen mereka terhadap calon presiden melalui penggunaan teknik klasifikasi deep learning dengan Convolutional Neural Network (CNN), ekstraksi fitur dengan metode Term Frequency-Inverse Document Frequency (TF-IDF), dan perluasan fitur dengan Word2Vec. Selain itu, penelitian ini juga menggunakan Particle Swarm Optimization sebagai teknik optimasi untuk meningkatkan performa model analisis sentimen. Hasil pengujian menunjukkan tingkat akurasi yang tinggi, memberikan gambaran yang komprehensif mengenai sentimen dan perspektif pengguna Twitter terhadap calon presiden 2024. Penelitian ini membantu memahami dinamika opini publik dalam konteks politik. Berdasarkan hasil evaluasi, penelitian ini menunjukkan nilai akurasi sebesar 78.2% dengan menggunakan Particle Swarm Optimization dengan kenaikkan 10.07% dari baseline.*

Kata Kunci*: CNN, Particle Swarm Optimization, sentimen, TF-IDF, Word2vec.*

INTRODUCTION

The rapid advancement of technology has become an integral part of society, as it is increasingly being used by people to simplify digital tasks. Technology enables individuals to express emotions through audio, video, and text on social media [1]. Every user can easily express their opinions or views through social media regarding any topic. Data from Twitter, such as complaints, information, and suggestions, can be utilized as a source to monitor public feedback [2]. Twitter has a massive user base and is preferred by users due to its ease of interaction and communication.

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Twitter is a social media application utilized by millions of users, serving as a platform for communication and expressing opinions on various subjects. Twitter serves as a unique and potentially powerful data source due to its ease of access, real-time nature, and richness in detail [3]. Twitter stands out as one of the most popular social media platforms among internet users due to its simplicity and user-friendly interface, allowing individuals the freedom to express their opinions openly [4]. Twitter users can easily stay informed about trending topics through the tweets of others at any given time.

Twitter serves as a platform for various activities, including public discussions, news dissemination, business promotions, sharing experiences, campaigns, and more. The data on Twitter is frequently used in sentiment analysis and research across various fields that require social media data analysis. Given the abundance of information on Twitter, determining public sentiment on specific topics can be challenging. Therefore, it will be utilized for this research by acquiring datasets from Twitter.

Sentiment analysis is a process utilized to discern public sentiment regarding a specific topic or reviews of particular products, employing Natural Language Processing (NLP) techniques to categorize them into positive, negative, or neutral values [5]. Sentiment analysis is an approach to analyzing text to recognize, categorize, and evaluate sentiments or emotions present in a text, such as tweets or reviews of a specific product. In social media, sentiment analysis can assist in identifying trends and public feelings. The abundance of public sentiment on social media can be utilized for research purposes.

Analysis can be conducted to monitor reputation, evaluate services to the public, and can be used to gauge public opinions on political issues or individuals. Although sentiment analysis has numerous benefits, several challenges need to be addressed when conducting sentiment analysis, such as the ambiguity of text and the use of informal language, which can impact the accuracy of sentiment analysis. However, with the advancement of natural language processing, sentiment analysis accuracy can be improved through various methods.

Sentiment analysis is conducted to understand the public sentiment on a specific topic. Analyzing sentiment on Twitter data has limitations due to the presence of unstructured text. However, the approach of TF-IDF (Term Frequency-Inverse Document Frequency) feature extraction is utilized to weigh each word, and Word2Vec expansion is employed to represent each word as a vector with semantic meaning. Data collection involves a crawling process to obtain tweet data from Twitter users. Sentiment analysis is performed to determine whether the public sentiment is positive or negative, and categorization is done using deep learning classification methods.

Deep learning is a branch of machine learning that incorporates multiple layers, including hidden layers. Commonly used types of deep learning include CNN (Convolutional Neural Network), LSTM, and RNN[6]. CNN, as one of the deep learning methods, consists of several layers, namely the convolutional layer, pooling layer, fully connected layer, and output layer. CNN employs multiple filters and is considered to have good accuracy compared to LSTM [7]. CNN is considered to have good accuracy, the use of Particle Swarm Optimization (PSO) optimization can help improve the accuracy of the CNN model's performance. PSO is an optimization method inspired by the behavior of a flock or a group of particles in searching for the optimal solution in a search space.

This research is based on various references from previous studies on sentiment analysis. Wongkar M and Angdresey A's study [8] involved text processing of data obtained using the naive Bayes method, utilizing a dataset from Twitter social media concerning presidential candidates in Indonesia for the 2019-2024 period. The study then compared the results with other methods such as SVM and KNN. Naive Bayes yielded an accuracy of 80.90%, while KNN achieved 75.58% accuracy, and SVM resulted in 63.99% accuracy. However, the method used only involved machine learning algorithms and did not include deep learning algorithms. Therefore, the upcoming research will attempt to incorporate deep learning algorithms with optimization.

Another study conducted by Que V, Iriani A, and Purnomo H [9] focuses on analyzing public sentiment regarding online transportation services using data from the Twitter platform and employing the SVM-PSO method. The research results indicate that the utilization of SVM-PSO produces a significant level of accuracy, which is significantly better compared to using SVM without PSO.

Another study conducted by Haque M, Akter Lima S, and Mishu S [7] compared classification using CNN and LSTM methods, with CNN demonstrating superior accuracy compared to LSTM without optimization. Based on previous research, the effectiveness of CNN is considered superior compared to other deep learning methods for classification. However, Particle Swarm Optimization (PSO) has not been extensively explored in conjunction with deep learning. Therefore, I propose conducting research focused on implementing Particle Swarm Optimization in CNN classification. This study aims to investigate the potential enhancements and optimization benefits that PSO can offer in the context of deep learning, specifically in the realm of CNN-based classification. The research aims to provide insights into the synergy between CNN and PSO, potentially yielding valuable findings for deep learning optimization techniques. selecting a Convolutional Neural Network (CNN) as a classification method is based on its effectiveness in processing structured data such as text. CNN is known to automatically extract important features from spatial data, in this case, referring to the representation of word sequences in text. The superiority of CNN in text classification tasks has been proven in various previous studies.

The selection of Particle Swarm Optimization (PSO) as an optimization method for CNN is motivated by its adaptive nature and its ability to efficiently search solution spaces. PSO is inspired by the collective behavior of particles working together to find optimal solutions. In the context of this research, PSO is expected to optimize CNN parameters, such as learning rate and the number of filters in the convolutional layer, to enhance the model's performance in sentiment classification on text data from Twitter. The combination of Word2Vec feature expansion and CNN classification with PSO is anticipated to yield accurate results.

MATERIALS AND METHODS

The presented flowchart illustrates the systematic process of conducting sentiment analysis research employing the Convolutional Neural Network (CNN) and Particle Swarm Optimization (PSO) methodologies, utilizing data extracted from the Twitter platform, as outlined in Figure 1.

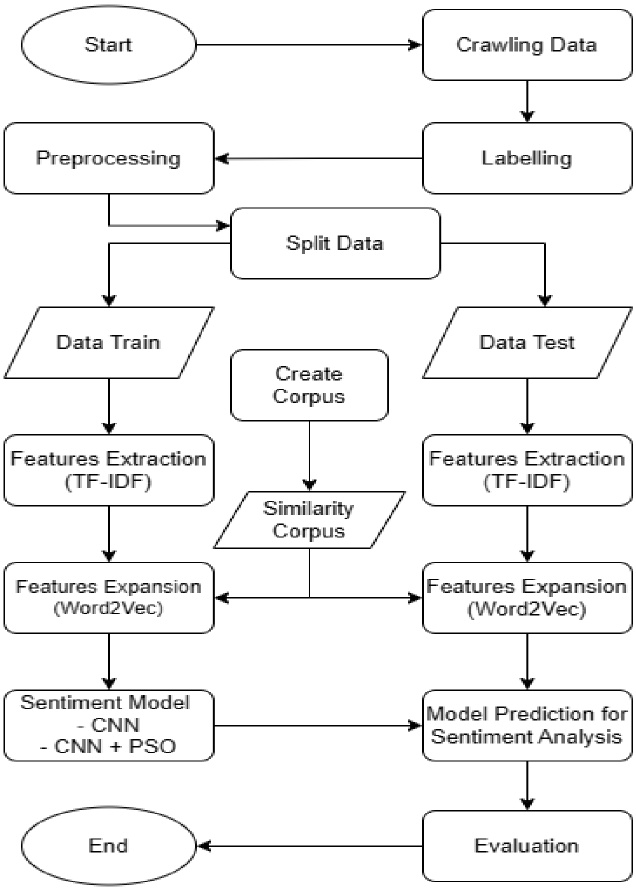

Figure 1. Research Methods

This visual representation provides a comprehensive overview of the sequential steps involved in the research methodology, encompassing data collection, preprocessing, model training, optimization, and evaluation phases.

1. Data Crawling

The results of tweets obtained from each Twitter user can be collected through the Twitter data crawling process. The data crawling process is initially required to connect to Twitter via the API (Application Programming Interface) using the Python programming language. The dataset used in this research consists of tweets that were trending

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in the year 2023, specifically related to the presidential candidates for 2024, with the extraction of 5 keywords including 'Ganjar Pranowo', 'Anies Baswedan', 'Prabowo Subianto', 'Calon Presiden' (Presidential Candidate), and 'Capres' (Presidential Candidate). The data obtained from Twitter, totaling 37,391 entries, will then proceed to the preprocessing stage.

Table 1. Total data by keyword

Keyword	Data
Anies Baswedan	10,434
Ganjar Pranowo	8,027
Capres	7,296
Calon Presiden	6,972
Prabowo Subianto	4,662
Total	37,391

2. Labeling

The labeling process in this study is conducted manually by three individuals. The data will then be assigned a value of -1, indicating a negative sentiment, or a value of 1 for tweets with a positive sentiment. The labeled data can be observed in Table 2.

Table 2. Quantity of Labeled Sentiment

Label	Quantity
Positive	21,866
Negative	15,525

3. Preprocessing

Preprocessing is the process of preparing data before it is processed in the next stages. Thus, it is expected that data that has undergone the preprocessing stage becomes clean and ready for further processing. The following are the stages of preprocessing:

A. Data Cleaning: Data cleaning is a process to remove punctuation marks, numbers, mentions, hashtags, and symbols.
B. Case Folding: Case Folding is the process of converting all uppercase letters into lowercase letters.
C. Tokenizing: Tokenization is the process of converting sentences into a collection of tokens or word segmentation.
D. Data Normalization: The procedure includes converting the written words into a standardized format following the general guidelines for Indonesian spelling (PUEBI). The objective is to facilitate comprehension and enhance the quality of analysis.
E. StopWord Removal: The StopWord Removal process is the process of extracting important words by eliminating those considered irrelevant and focusing on more significant words.
F. Stemming: Stemming involves eliminating basic words, such as removing suffixes, prefixes, confixes, and infixes.

4. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a method belonging to the realm of deep learning [10]. It is a neural network architecture extensively utilized in image processing, pattern recognition, and text classification [11], [12]. CNN excels at learning interconnected features and merging them for effective classification. In Natural Language Processing (NLP), visuals are substituted with documents containing textual content, represented as matrices. Each row signifies a word in a sentence, while columns represent the dimensions of that word. The illustration below showcases text classification using CNN [13]. The method section contains paragraphs on research design,

The CNN for text classification consists of several layers, namely the Embedding layer, which functions to transform each word into a vector representation through the embedding process; the Convolutional layer, which serves to classify text and extract features from the text that has passed through the embedding layer to detect important patterns and generate a feature map; the Pooling layer, which works to reduce the size of the input data and extract the maximum value from each region in the feature map; and the Fully Connected layer, which functions to convert the feature map into a vector by flattening its dimensions.

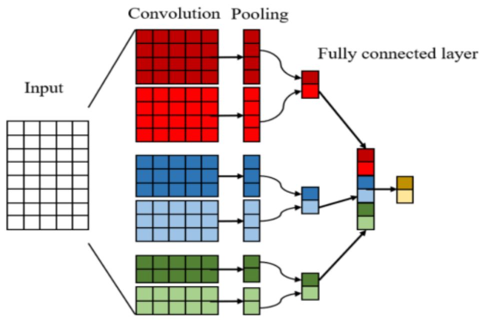

Figure 2. Text Classification using CNN

5. TF-IDF

TF-IDF, or Term Frequency-Inverse Document Frequency, is a method utilized in text processing and document analysis to assess the importance level of a word within a document or a collection of documents (corpus). Widely employed as a feature extraction technique in text processing, TF-IDF amalgamates two key concepts: Term Frequency, measuring how often a word appears in a document, and Inverse Document Frequency, representing the reciprocal of the word's frequency across documents. TF is used to measure how often a term appears in a document [14]. Term Frequency calculates the frequency of a word in a document by dividing the number of occurrences by the total word count in the document. The formula for TF-IDF weighting is as follows:

$$Wij = tf_{ij} * Idf_j , Idf_j = \left(log\left(\frac{N}{df}\right)\right) \quad (1)$$

With W_{ij} representing the weight of the i-th term in document j, where tf_{ij} is the frequency value of the term in a specific document, and Idfj is the value of Inverse Document Frequency (IDF).

6. Word2Vec

The Word2Vec machine learning model is employed to generate vector representations of words from text[15]. Word2Vec provides better performance for semantic tasks in determining the association of a word with other similar words [16]. Created by Tomas Mikolov and his team at Google, Word2Vec aims to capture the meaning of words in a given context and produce vector representations with semantic properties. This model signifies a significant breakthrough in the field of natural language processing and has been applied in various applications such as text analysis, language modeling, and semantic understanding. Word2Vec word embeddings are often used as feature expansion for various text classifications.

7. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an optimization method inspired by the behavior of a swarm or a group of particles in searching for an optimal solution within a search space. However, the PSO method has become a popular choice for addressing complex and non-linear optimization problems. Each particle in Particle Swarm Optimization possesses a particle velocity moving in the search space, with a dynamically adjusted speed based on historical behavior[17]. Each particle tends to move towards a better search area during the search process.

8. Confusion Matrix

The Confusion Matrix is a method used to evaluate the performance of classification methods. It consists of four parts: True Positive (TP), which are instances truly belonging to the positive class and correctly predicted as the positive class; True Negative (TN), which are instances truly belonging to the negative class and correctly predicted as the negative class; False Positive (FP), which are instances truly belonging to the negative class but incorrectly predicted as the positive class; False Negative (FN), which are instances truly belonging to the positive class but incorrectly predicted as the negative class. The Confusion Matrix can be utilized to calculate model evaluation metrics such as accuracy, precision, recall, and F1-score. Accuracy measures how well the model predicts overall correctness. Precision assesses how well the model predicts positive instances correctly among all predictions classified as the positive class. Recall measures the correctly classified positive instances and compares them to the overall total. F1-Score provides a balanced measurement between precision and recall.

RESULTS AND DISCUSSION

A. First Scenario of Baseline Performance with CNN

This scenario is conducted to determine the optimal data division by comparing training and test data, aiming to achieve the highest accuracy. Various data split scenarios are applied with ratios of 90:10, and 80:20. The results obtained from scenario 1 are presented in Table 3.

Table 3. Result of Scenario 1

Test Size	Accuracy(%)	F1-Score(%)
80:20	67.54	64.2
90:10	**68.13**	**64.2**

Based on the analysis results, which involved varying test sizes, it was observed that the test size of 90:10 yielded the highest accuracy and F1 score values. This particular test size demonstrated superior performance compared to others, and as a result, it has been chosen to be employed in the subsequent experimental scenario. This decision is based on the aim of optimizing the model's performance by selecting a test size that consistently produces favorable evaluation metrics. The utilization of a 90:10 test size is expected to contribute positively to the overall reliability and effectiveness of the classification model in the next stage of the research.

B. Second Scenario of TFIDF Feature Extraction

In the second experimental scenario, the utilization of TF-IDF feature extraction with adjusted max features was explored. This exploration aimed to investigate the impact of adjusting the max features parameter on the accuracy and F1 score of the classification model. The results of this scenario, including the achieved accuracy and F1 score values, are presented in Table 4.

Table 4. Result of Scenario 2

Max Features	Accuracy(%)	F1-Score(%)
500	70.5(+2.37)	69.7(+5,5)
1000	70.8(+2.67)	70.2(+6)
3000	71.5(+3,37)	71.3(+7,1)
5000	72.0(+3,87)	71.6(+7,4)
10000	**73.4(+5,27)**	**72.3(+8,1)**
15000	72.5(4.37)	72.3(+8.1)

This result provides a comprehensive overview of the performance of the model when TF-

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IDF feature extraction is applied with varying max features. The detailed insights obtained from this scenario contribute valuable information for understanding the influence of adjusting the max features parameter on the classification model's effectiveness.

C. Third Scenario of Feature Expansion Word2Vec

In the third experimental scenario, the exploration focused on feature expansion using Word2Vec, considering a comparison across three different corpus. These corpus include the dataset from Indonews, followed by the dataset from Twitter, and finally, a combined corpus comprising both Twitter and Indonews corpus. The objective was to investigate how the variation in corpus composition impacts the accuracy and F1 score of the classification model. The results of this scenario, encompassing the achieved accuracy values, are comprehensively presented in Table 5, and the F1 Score value, is comprehensively presented in Table 6. This table serves as a valuable reference for understanding the influence of corpus variation on the performance of the classification model.

Table 5. Accuracy Corpus Comparison

Top (n)	Accuracy(%)		
	Indonews	Tweet	Indonews + Tweet
1	71.7(+3.57)	72.4(+4,27)	73.3(+5,17)
2	71.8(+3.67)	72.5(+4,37)	73.4(+5,27)
3	72.1(+3.97)	71.5(+3,37)	73.4(+5,27)
5	73.5(+5.37)	72.3(+4,17)	**74.4(+6,27)**
10	73.3(+5,17)	72.0(+3,87)	71.6(+3,47)

Table 6. F1 Score Corpus Comparison

Top (n)	F1 Score(%)		
	Indonews	Tweet	Indonews + Tweet
1	71.3(+7.1)	72.1(+7,9)	72.9(+8,7)
2	71.4(+7.2)	72.2(+8)	73.0(+8.8)
3	71.8(+7.6)	71.5(+7.3)	73.0(+8.8)
5	73.1(+8.9)	72.0(+7.8)	**74.0(+9.8)**
10	73.3(+9.1)	71.3(+7.1)	71.2(+7)

The highest accuracy and optimal F1 score are achieved in the Top 5. This outcome indicates that incorporating corpus with a combination of Indonews and Tweet enhances the model's ability to classify sentiment more effectively. Therefore, the combination of both corpus positively contributes to the model's performance, providing a better understanding.

D. Fourth Scenario (PSO)

In the fourth experimental scenario, the application of Particle Swarm Optimization (PSO) was explored, specifically focusing on the optimization of parameters for Convolutional Neural Network (CNN). This scenario aimed to leverage PSO in searching for the best set of parameters that would enhance the performance of the CNN model. The optimization process included a comparison between default learning rates and optimal learning rates. The results of this scenario, encompassing the obtained values for accuracy and F1 score, are meticulously presented in Table 7.

Table 7. Result of Scenario 4

	Accuracy(%)	F1-Score(%)
Default Learning Rate	76.8(+8.67)	76.6(+12.4)
Optimal Learning Rate	**78.2(+10.07)**	**77.7(+13,5)**

By employing all four scenarios, improvements were observed in each scenario, starting from the first scenario that solely utilized CNN, followed by the second scenario incorporating TF-IDF feature extraction, then the third scenario involving word2vec feature expansion, and finally, the fourth scenario implementing particle swarm optimization. Each scenario demonstrated an increase in both accuracy and F1 score, as depicted in Figures 3 and 4.

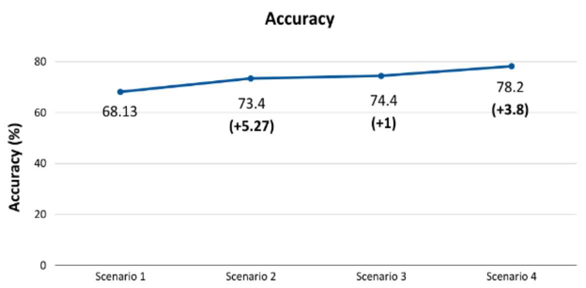

Figure 3. Accuracy of All Scenario

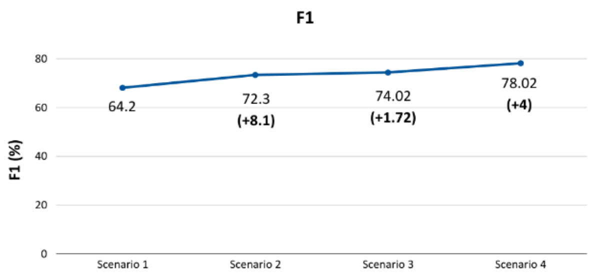

Figure 4. F1-Score of All Scenario

CONCLUSION

Sentiment analysis was under taken using a Twitter dataset comprising 37,391 entries and employing 5 predefined keywords. The analysis encompassed the utilization of classification through Convolutional Neural Network (CNN), feature extraction employing TF-IDF, feature expansion using Word2Vec with 3 corpus, and optimization through Particle Swarm Optimization (PSO). The utilization of Particle Swarm Optimization (PSO) yielded the highest accuracy, reaching 78.2%, showcasing a notable increase of 10.07% compared to the baseline. The research outcomes revealed that Particle Swarm Optimization not only produced the highest accuracy and F1 score values but also exhibited a substantial and notable improvement compared to other methods, namely CNN, TF-IDF, and Word2Vec. This suggests that the application of PSO plays a pivotal role in significantly enhancing the sentiment analysis model's performance. For recommendation, future research could further explore various combinations of methods and parameters to achieve more optimal results. Additionally, employing broader datasets and diversifying topics may enhance the model's generalization for more common situations. This research provides a foundation for further development in enhancing sentiment analysis reliability on social media, particularly on the Twitter platform.

REFERENCE

[1] K. Sailunaz and R. Alhajj, "Emotion and sentiment analysis from Twitter text," *J Comput Sci*, vol. 36, p. 101003, 2019, doi: 10.1016/j.jocs.2019.05.009.

[2] N. L. P. C. Savitri, R. A. Rahman, R. Venyutzky, and N. A. Rakhmawati, "Analisis Klasifikasi Sentimen Terhadap Sekolah Daring pada Twitter Menggunakan Supervised Machine Learning," *Jurnal Teknik Informatika dan Sistem Informasi*, vol. 7, no. 1, pp. 47–58, 2021, doi: 10.28932/jutisi.v7i1.3216.

[3] O. Edo-Osagie, B. De La Iglesia, I. Lake, and O. Edeghere, "A scoping review of the use of Twitter for public health research," *Comput Biol Med*, vol. 122, no. April, p. 103770, 2020, doi: 10.1016/j.compbiomed.2020.103770.

[4] W. G. Angelina Puput Giovani, Ardiansyah, Tuti Haryanti, Laela Kurniawati, "Analisis Sentimen Aplikasi Ruang Guru di Twitter Menggunakan Algoritma Klasifikasi," *TEKNOINFO*, vol. 14, no. 2, pp. 116–124, 2020, doi: https://doi.org/10.33365/jti.v14i2.679.

[5] R. Kumar and S. Garg, "Aspect-Based Sentiment Analysis Using Deep Learning Convolutional Neural Network," *Advances in Intelligent Systems and Computing*, vol. 933, pp. 43–52, 2020, doi: 10.1007/978-981-13-7166-0_5.

[6] M. E. Basiri, S. Nemati, M. Abdar, E. Cambria, and U. R. Acharya, "ABCDM: An Attention-based Bidirectional CNN-RNN Deep Model for sentiment analysis," *Future Generation Computer Systems*, vol. 115, pp. 279–294, 2021, doi: 10.1016/j.future.2020.08.005.

[7] M. R. Haque, S. Akter Lima, and S. Z. Mishu, "Performance Analysis of Different Neural Networks for Sentiment Analysis on IMDb Movie Reviews," *3rd International Conference on Electrical, Computer and Telecommunication Engineering, ICECTE 2019*, pp. 161–164, 2019, doi: 10.1109/ICECTE48615.2019.9303573.

[8] M. Wongkar and A. Angdresey, "Sentiment Analysis Using Naive Bayes Algorithm Of The Data Crawler: Twitter," *Proceedings of 2019 4th International Conference on Informatics and Computing, ICIC 2019*, pp. 1–5, 2019, doi: 10.1109/ICIC47613.2019.8985884.

[9] V. K. S. Que, A. Iriani, and H. D. Purnomo, "Analisis Sentimen Transportasi Online Menggunakan Support Vector Machine Berbasis Particle Swarm Optimization," *Jurnal Nasional Teknik Elektro dan Teknologi Informasi*, vol. 9, no. 2, pp. 162–170, 2020, doi: 10.22146/jnteti.v9i2.102.

[10] A. Pambudi and S. Suprapto, "Effect of Sentence Length in Sentiment Analysis Using Support Vector Machine and Convolutional Neural Network Method," *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, vol. 15, no. 1, p. 21, 2021, doi: 10.22146/ijccs.61627.

[11] G. A. M. Kukuh Jaluwana, Gusti Made Arya Sasmita, and I Made Agus Dwi Suarjaya, "Analysis of Public Sentiment Towards Goverment Efforts to Break the Chain of Covid-19 Transmission in Indonesia Using CNN and Bidirectional LSTM," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 6, no. 4, pp. 511–520, 2022, doi: 10.29207/resti.v6i4.4055.

[12] A. Z. R. Adam and E. B. Setiawan, "Social Media Sentiment Analysis using Convolutional Neural Network (CNN) dan Gated Recurrent Unit (GRU)," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI)*, vol. 9, no. 1, pp. 119–131, 2023, doi: 10.26555/jiteki.v9i1.25813.

[13] F. Alfariqi, W. Maharani, and J. H. Husen, "Klasifikasi Sentimen pada Twitter dalam Membantu Pemilihan Kandidat Karyawan dengan Menggunakan Convolutional Neural Network dan Fasttext Embeddings," *e-Proceeding of Engineering*, vol. 7, no. 2, pp. 8052–8062, 2020, [Online]. Available: https://www.alexa.com/siteinfo/twitter.com

[14] W. A. Prabowo and F. Azizah, "Sentiment Analysis for Detecting Cyberbullying Using TF-IDF and SVM," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 4, no. 6,

VOL. 9. NO. 2 FEBRUARY 2024
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pp. 11–12, 2020, doi: 10.29207/resti.v4i6.2753.

[15] H. Utama and A. Masruro, "Analisis Sentimen pada Twitter menggunakan Word Embedding dengan Pendekatan Word2Vec," *Jurnal Sistem Cerdas*, vol. 5, no. 2, pp. 128–134, 2022, doi: 10.37396/jsc.v5i2.242.

[16] D. E. Cahyani and I. Patasik, "Performance comparison of tf-idf and word2vec models for emotion text classification," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 5, pp. 2780–2788, 2021, doi: 10.11591/eei.v10i5.3157.

[17] G. G. S. Putra, W. Swastika, and P. L. T. Irawan, "Perbandingan Particle Swarm Optimization dengan Genetic Algorithm dalam Feature Selection untuk Analisis Sentimen pada Permendikbudristek PPKS-LPT," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 8, no. 3, pp. 412–421, 2022, http://dx.doi.org/10.26418/jp.v8i3.57300.