ISSN 2502-5872 (Print)
ISSN 2622-3627 (Elektronik)

Volume 8 Number 3, August 2023, 1169-1182

COMPARISON OF LSTM AND GRU METHODS IN SENTIMENT ANALYSIS OF SATUSEHAT APPICATION REVIEW

Hedy Leoni Asudi[1*], Ema Utami[2], Anggit Dwi Hartanto[3]
[1,2,3]Department of Informatics Engineering, Universitas Amikom Yogyakarta, Yogyakarta Province, Indonesia

*Correspondence: hedyleoni@students.amikom.ac.id

ABSTRACT

This article describes a comparison between the LSTM and GRU methods in sentiment analysis. Both methods were chosen based on the simplicity of the model and are considered capable of processing relatively long data. the dataset used in this study amounted to 12260 data obtained from scraping on the Google Play site using google-play-scraper library. In analyzing Sentiments, 2 Deep Learning methods are used, namely LSTM and GRU. From the results The GRU accuracy value reaches 91% while the LSTM accuracy value is 89%. However, for the Recall and F1-score tests, these two methods still get low scores in analyzing positive data.

Keywords: Sentiment, Classification, LSTM, GRU, SatuSehat

How to Cite: Asudi, H. L., Utami, E., & Hartanto, A. D. (2023). Comparison of LSTM and GRU Methods in Sentiment Analysis of Satusehat Appication Review. *Mathline: Jurnal Matematika dan Pendidikan Matematika*, *8*(3), 1169-1182. http://doi.org/10.31943/mathline.v8i3.475

PRELIMINARY

At this time the growth of data on web pages, e-commerce, e-health and social media is growing rapidly. Due to the increasing complexity of the computational process and the large amount of data in *the Corpus*, it is recommended to use deep learning models such as Long Short Term Memory (LSTM), Recurrent Neural Network (RNN), Convolution Neural Network (CNN) and Gated Recurrent Unit (GRU) because of the deep learning model It makes it possible to perform complex computational tasks and provide more memory space than conventional Machine Learning (Santur, 2019).

Sentiment analysis is one of the well-known fields in the field of natural language preprocessing (NLP) and data mining (Haque et al., 2019; Yadav & Vishwakarma, 2020; Birjali et al., 2021). Sentiment analysis aims to understand, extract and manage textual information automatically to find out a sentiment is negative, positive or neutral (Paputungan, 2021). Sentiment assessment is used to collect and review viewpoints about products and services through tweets, reviews, comments and blog posts (Muhammad, 2021). Google Play is a digital service owned by Google that provides various services of application products, games, music, songs, books and media players (Mustopa et al., 2020) On Google play there is a review feature so that application users can send reviews in the form of criticism, suggestions, praise and other assessments of the application (Fransiska, 2020). Users can also provide ratings in the form of star scores in the range of 1 to 5. (Mustopa et al., 2020) App user reviews can provide informative evidence making it an important element in app development (Pratama, 2019).

Research on sentiment analysis using deep learning methods includes sentiment analysis research that compares LSTM and Naive bayes models to analyze 1000 novel review data on goodread.com sites. From the results of sentiment analysis carried out, LSTM using 1 layer obtained an accuracy of 71.20%, LSTM using 2 *Layers* obtained an accuracy of 72.85% and Naive Bayes obtained the lowest result of 67.88% (Nurrohmat & SN, 2019). Research from Aslam on Research from Aslam tested the LSTM, GRU and also LSTM-GRU Models to analyze sentiment and detect emotions from cryptocurrency-related tweets. The data amounted to 40,000 tweet data collected using scrapping techniques using the *Tweepy data library* collected based on #cryptocurrency, #crypromarked and #BTC hashtags, the data was divided into 34,000 training data and 6,000 testing data. The results of the LSTM model sentiment analysis test results get an accuracy value of 99%, precision 98%, recall 97%, F1 97% and G mean 97%, for the GRU model get an accuracy value of 98%, precision, 98%, recall 97%, F1 98% &; G mean the last is the LSTM-GRU model gets an accuracy value of 99%, precision 99%, recall 98%, F1 98% and G mean 98% of the test results concluded LSTM and LSTM-GRU models have the highest accuracy results but the LSTM-GRU model is slightly more superior in precision, recall, F1 and G mean (Aslam, et al., 2022).

The previous research using the LSTM model, namely Movie Review Sentiment Analysis Using Word2Vec and the LSTM Deep Learning method, in this study the lowest accrual results reached 85.86% and the highest accuracy reached 88% (Yu et al., 2019; Muhammad et al., 2021).

SatuSehat is an application developed by the Ministry of Communication and Information Technology of the Republic of Indonesia (KOMINFO) which can be downloaded on *Goggle Play* (Mustopa et al. , 2020) . In addition to functioning as a *Contact Tracing* application, SatuSehat also functions as an electronic vaccination card storage (Illia et al., 2021).

On September 3, 2021, news spread about the leak of vaccination data which had an impact on public opinion of the SatuSehat application (Illia et al., 2021) . As for the opinions of SatuSehat application users such as inaccurate in telling the location of red, yellow and green zones, the application consumes many kouta and cellphone batteries because it is required to continue to activate Bluetooth and notifications that keep ringing, short user sessions that result in the account logging out automatically so that the OTP code must be entered repeatedly and a decrease in speed in internet access (Mustopa et al., 2020a) To analyze the opinions of SatuSehat users, a sentiment analysis research is needed (Doloksaribu & Samuel, 2022). From the results of sentiment analysis research, it is hoped that improved application quality and preformace (Imanuddin et al., 2023). The previous research that also discussed sentiment analysis from SatuSehat application users was the Anaysis of User Review for The SatuSehat Application on Google Play Using the Support Machine and Naïve Bayes Algorithm Based Particle Swarm Optimization which analyzed 1364 Google Play user reviews using the Naïve Bayes and SVM algorithms (Mustopa et al., 2020)

Sentiment Analysis on SatuSehat Application Using TextBlob and VADER Library The study analyzed 9,820 tweet data from Twitter using TextBlob and VADER, but this study did not use an evaluation model. (Illia et al. , 2021) . However, on March 1, 2023, SatuSehat has now changed its name to Satusehat. In the Satusehat application, users can not only access the previous features, namely COVID 19 vaccination certificates, PCR and antigen test results, scan QR codes when checking in at public places. But in the future there is a health diary feature that can record health conditions such as height and weight reduction, blood pressure, heart rate and blood sugar of application users and those closest to them (Kemenkes, 2023).

In this study, SatuSehat application user sentiment will be classified into positive and negative and determine the best model from 2 methods, namely LSTM and GRU in analyzing SatuSehat application user sentiment.

METHODS

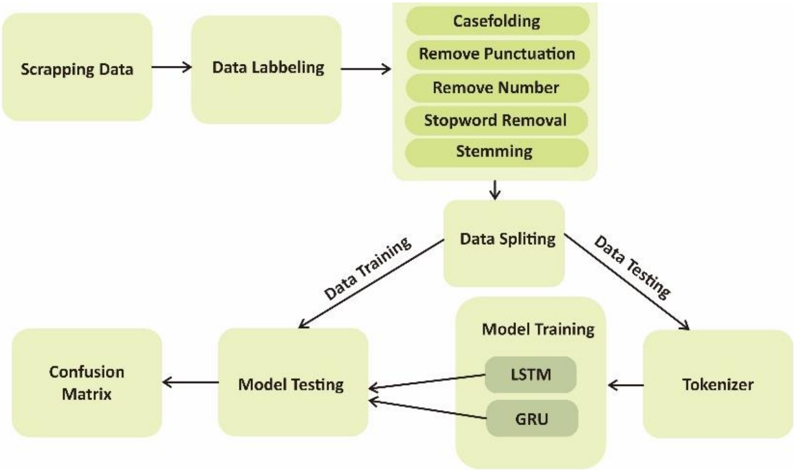

Figure 1. Research Flow

1. Data Collection

Based on Figure 1, the first process in this study is collecting data. The data used is SatuSehat Application user review data obtained through scrapping techniques from the Google Play website. The review data obtained amounted to 12260 data derived from user reviews of the SatuSehat application on March 1, 2020-March 11, 2023. This research uses the google-play-scraper library provided by open source on pypi.org website. The google-play-scraper library itself allows researchers to extract data in the form of information related to applications, review times, application reviews, ratings, response time from developers, replies from application version developers, images from users, and usernames who provide reviews (Wijaya, 2022).

2. Data Labeling

Data is labeled positive or negative based on the rating variables in the review data. Data whose ratings are 1 to 3 are negative while data whose ratings are 4 and 5 are positive. This study does not classify data as neutral because it is considered less informative because the review is dominated by the word criticism and praise for the application (Fransiska, 2020; Chlap et al., 2021).

3. Preprocessing

Preprocessing is a technique used to clean data in order to minimize the learning process of the model (Soni et al., 2020; Aslam et al., 2022). The process contained in preprocessing, namely Case Folding, is a process to change all letters in the review data to *lowercase* (Doloksaribu, 2022), Punctuation Removal is a process to remove symbols that are often found in data such as commas, question marks, colons, semicolons and so on (Aslam et al., 2022), Number Removal is to cross numbers contained in data that have no meaning in the data modeling process(Aslam et al., 2022), Stopword removal is a process of words that have no impact on a sentence being eliminated (Hendriyanto, 2022) and Stemming is the process of a word that has affixes mapped and deciphered and then converted into a base word (Subagja, 2021)

4. LSTM

The Recurrent Neural Network (RNN) is a popular ANN design. In RNN, there is a relationship between units that create a loop, allowing information to flow from the output unit to the input unit (Hidayat & Mustawinar, 2022). LSTM is a developed version of RNN that allows processing relatively long-term data (M.R Haque, 2019). There are 3 Main Gates in LSTM, the first is the Forgot Gate Layer which is *a* sigmoid layer that determines what information is removed from memory cells, the second is the Input Gate Layer what new information will be stored in memory cells and the last is the Output Gate Layer which determines the output of LSTM cells. Mathematically, Gate in LSTM can be defined as follows:

$$F_t = \sigma(W_f . [h_{t-1}, X_t] + b_f)$$

$$I_t = \sigma(W_i . [h_{t-1}, X_t] + b_f)$$

$$O_t = \sigma(W_o . [h_{t-1}, X_t] + b_o)$$

$$h_{t=}O_t * \tanh()C_t$$

Where, and describes forget, input and output $F_t I_t O_t$*gates*. Layer and describes the refractive factor contained in the $b_f b_o$ *layer*. represents the input and output of the current unit. is the output of the previous input. symbolizes X_t dan $h_t h_{t-1} \sigma$ *the sigmoid layer with a sigmoid* activation function and *tanh* is a *tanh layer* with an than activation function *(M.R Haque, 2019).*

5. GRU

GRU is like LSTM which uses a gate system but the GRU architecture is simpler because it does not use *cell* state, In GRU architecture hidden state serves to store information, reset state serves to determine incoming information should be forgotten or not, and update gate serves to remember information (Shahid et al., 2020; Zaman, Sumpeno and Hariadi, 2019).

The reset gate unit on the GRU is symbolized by and the update gate unit is symbolized by , is the input at moment $r_t Z_t X_t t$. The function of the GRU method is symbolized as follows (Yongping Xing, 2019):

$$r_t = \sigma(++) W_{rh} h_{t-1} W_{rs} x_t b_r$$

$$z_t = \sigma(++)W_{rh}h_{t-1}W_{zx}x_t b_z$$

$$\tilde{h}_t = \tanh(++)W_{hh}(r_t * h_{t-1})W_{xh}x_t b_h$$

$$h_t = (+1 - z_t) * h_{t-1}z_t *_t \tilde{h}$$

$$\sigma_t = \sigma(W_0 \cdot h_t)$$

6. Confusion Matrix

Confusion matrix is used to measure performance in classification systems. (Xu, 2020; Rahmad et al., 2020) Confusion matrix castrated from 4 representations of results, namely True Positive (TP), False Positive (FP), True Negetive (TN) and False Negative (FN) (Adyatma Subagja et al., 2021). True Negative (TN) value is the amount of negative data detected as true, False Positive (FP) is negative data detected as positive data. True Positive (TP) is positive data that is detected as true and False Negative (FN) is the opposite of True Positive.

The following is a formula of values to calculate accuracy results, *Recall*, and precision based on results *True Positive (Tp), False Positive (Fp), True Negetive* (*Mr*) and *False Negative* (*Fn*) (Ali Kandhro et al., 2019).

$$\text{Accuracy} = \frac{Tp + Tn}{Tp+Fp+Tn+Fn}$$

$$\text{Precision} = \frac{Tp}{Tp+Fp}$$

$$\text{Recall} = \frac{Tp}{TP+Fn}$$

$$\text{F-Score} = 2\text{x}\frac{Recall^{*}\,Akurasi}{Recall+Akurasi}$$

Accuracy is the value of the similarity between the predicted value and the actual value. Precision is the level of correctness of the information requested by the user and provided by the system. Recall is the success rate of the system in finding information. F-measure is a combination of recall and precision to determine the success of the retreat (Monday, 2022).

RESULT AND DISCUSSION

1. Data collection

Data collected from scraping results amounted to 12260 data obtained using scrapping techniques using the google-play-scraper library. Figure 2 displays the top 10 datasets from 12260 data consisting of "comment" which contains user reviews in text form and "score" which contains user reviews in the form of ratings from the range of 1-5. In figure 3 is a bar chart of the number of rating distributions given by application users from the range of 1-5, it can be seen that many ratings are given by users, namely 5 and 1. Based on the graph, rating 1 is the most rating given by SatuSehat application users reaching 8000, then rating 5 which is the second most rating which amounts to 2000, rating 2 reaching 1000. 3 and 4 which does not reach 1000.

	content	score
0	Makin ksni makin ga jelas hadeh. Udh di update...	1
1	Ok cepat respon nya kita harap kan utk kedepan...	5
2	saya lupa akun dan no tidak aktip lagi ga bisa...	1
3	Bagus	1
4	semoga lancar apknya	5
5	Sehat	5
6	Login gk bisa, pas daftar tulisan nya user alr...	1
7	bagus	5
8	Saya sudah boster ke 2 mau ngekla sertifikat n...	5
9	Data sertifikat vaksin muncul data orang lain....	1

English Version :

	content	score
0	The more you come here, the more unclear it is...	1
1	Ok quick response we hope to come forward	5
2	I forgot my account and I can't register anymore	1
3	Good	1
4	I hope the app goes smoothly	5
5	Healthy	5
6	Login can't, when the list of writing the user...	1
7	Good	5
8	I have boster to 2 want to claim the certifica...	5
9	Vaccine certificate data appears other people'...	1

Figure 2. SatuSehat Dataset

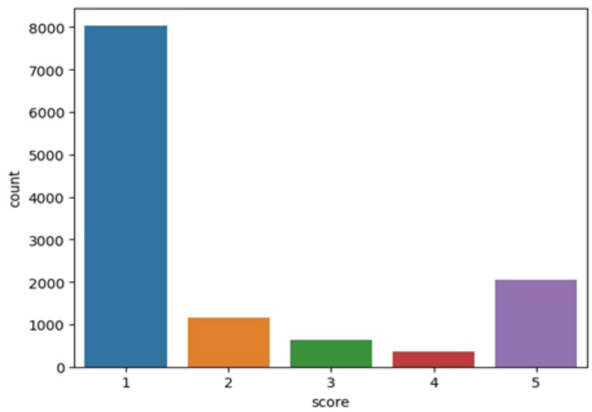

Figure 3. User SatuSehat Rating Bar Chart

2. Data Labelling

In Figure 4. Is the number of rating distributions given by application users from the range of 1-5, it can be seen that many ratings are given by users, namely 5 and 1. Based on these ratings, labelling ratings 1 to 3 is negative and ratings 4 and 5 are positive. From the results of data labelling, the results can be seen in Figure 4, positive data amounted to 19.7% and negative data amounted to 80.3%.

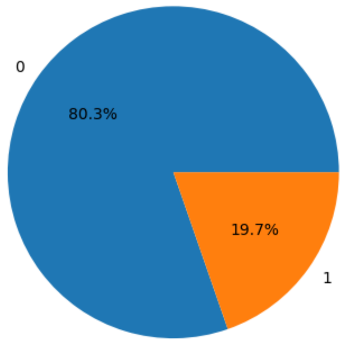

Figure 4. Data labels

3. Preprocessing

The first step in the preprocessing process is case folding which aims to change the text in the comment column into lowercase, then after the text becomes lowercase, the punctuation removal stage is carried out to remove punctuation marks and symbols contained in the text, stop word removal, stemming.

4. Model Training

Before the data training process, a data sharing process is carried out that will be used in the training process and model testing. As much as 80% of the data is used for the training process and 20% of the data is used for the model testing process. 80% of the dataset or 9808 data was used for model training of LSTM and GRU deep learning methods with 100 neurons, Dropout 0.2, learning rate 0.01, number of epoch 5, batch size of 50 and validation data of 20% of the training data.

5. Model Testing

In the second testing phase, the trained model will be tested using the confusion matrix method by testing accuracy, recall, precision and F1-score.

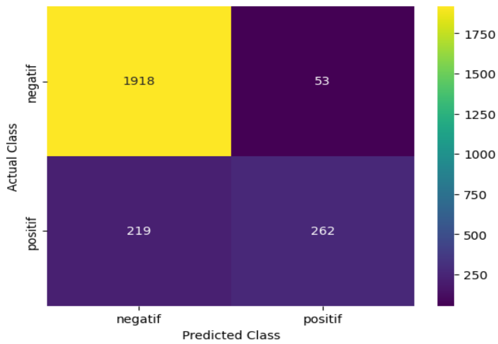

Figure 5. Confusion Matrix LSTM

a. Accuracy Testing

LSTM accuracy testing based on cofusion matrix in Figure 5 with formulas Accuracy =$\frac{Tp+Tn}{Tp+Fp+Tn+Fn}$. The results of accuracy testing can be seen below :

$$\textbf{\textit{Accuracy}} = \frac{1918+262}{2451} \text{x}100$$

$$= \frac{2180}{2452} \text{x}100 = 89\%$$

b. Precision Testing

Precision Testing by using formulas Precision = $\frac{Tp}{Tp+Fp}$ The results of precision testing can be seen in Table 1 below:

Table 1. LSTM Precision Testing

	Negative	*Positive*
TP	***1918***	***262***
TP+FP	***1918+219***	***262+53***
precision	***1918/2137*100 = 90%***	***262/315*100 = 83%***

c. Recall Testing

Recall testing by using formulas Recall = $\frac{Tp}{TP+Fn}$ The results of the recall test can be seen in Table 2 below:

Table 2. LSTM Recall Testing

	Negative	*Positive*
TP	***1918***	***262***
TP+FN	***1918+53***	***262+219***
Recall	***1918/1971*100 = 97%***	***262/481*100 = 54%***

d. F1score

F1 score (F-score) testing by using the formula F-Score = 2x$\frac{Recall^{*} Akurasi}{Recall+Akurasi}$ F1-score test results can be seen in Table 3 below:

Table 3. LSTM F1 Score Testing

	Negative	*Positive*
Recall	***90***	***54***
precision	***97***	***83***
F1 score	***2*(90*97)/(90+97)= 93%***	***2*(54*83)/(54+83)=65%***

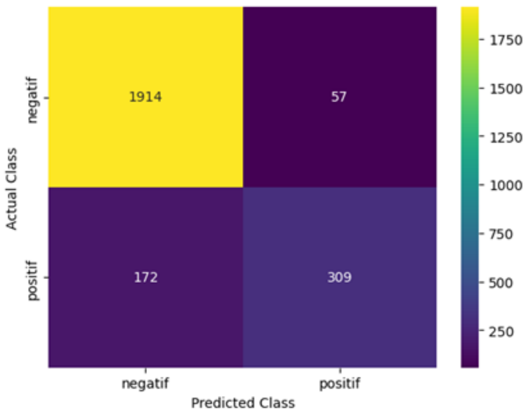

Figure 6. GRU Cofusion Matrix

e. GRU Accuracy Testing

GRU accuracy testing based on cofusion matrix in figure 6 with formulas Accuracy $=\frac{Tp+Tn}{Tp+Fp+Tn+Fn}$The results of accuracy testing can be seen bellow :

Accuracy $=\frac{1914+309}{2451}$x100

=2223/2452 x100=91%

f. GRU Precision Testing

Precision Testing by using formulas Precision = $\frac{Tp}{Tp+Fp}$ The results of precision testing can be seen in Table 4 below:

Table 4. GRU Precision Testing

	Negative	*Positive*
TP	***1914***	***309***
TP+FP	***1914+172***	***309+57***
Presisi	***1914/2086*100 = 92%***	***309/364*100 = 84%***

g. GRU Recall Testing

Recall testing by using formulas Recall = $\frac{Tp}{TP+Fn}$ The results of recall testing can be seen in Table 5 below:

Table 5. GRU Recall Testing

	Negative	*Positive*
TP	***1914***	***309***
TP+FN	***1914+57***	***309+172***
Recall	***1914/1971*100 = 97%***	***309/481*100 = 64%***

h. GRU F1score

F1 score (F-score) testing by using the formula F1-Score = 2x$\frac{Recall^{*}\ Akurasi}{Recall+Akurasi}$ F1-score test results can be seen in Table 6 below:

Table 6. GRU F1 Score Testing

	Negative	*Positive*
Recall	***97***	***64***
Presisi	***92***	***84***
F1 score	***2*(97*92)/(97+92)= 94%***	***2*(64*84)/(64+84)=73%***

Based on the test results of the two LSTM and GRU models, the accuracy value of the model using the GRU deep learning method is superior to LSTM. The GRU accuracy value reaches 91% while the LSTM accuracy value is 89%. The accuracy value of both models is quite high, but in recall testing in the positive data class, the value is still relatively low.

i. Word cloud

A word cloud is an image that shows a list of words contained in a text in the form of an intuitive visual abstraction. When words are often used in text, the form of word representation is greater in an image (Fahrudin, 2022). In this study, word clouds are divided into two of the positive and negative categories that can be seen in Figure 7, namely word clouds derived from negative sentiments and Figure 8 from the Positive category

Figure 7. World cloud results from negative sentiment

Figure 8. World cloud results from positive sentiment

CONCLUSION

From the test results, it can be concluded that models with LSTM and GRU methods have the same accuracy results in sentiment analysis but LSTM is slightly superior in precision, recall and F1-score. From both models, it can be concluded that both are superior in analyzing negative sentiments.

The obstacle of this study is that there are users who give critical comments but give a rating of 4 or 5. From the results of *the word cloud*, negative reviews contain several user complaints while using the SatuSehat application, such as after being updated, users have difficulty opening the application and some have difficulty *logging in*. User complaints are evidenced by words that have a high frequency in the negative sentiment class ‘aplikasi’, ‘*update’*,’buka’, ‘masuk’ dan ‘*login’*. From the results of the *positive word cloud* contains user praise for the application as evidenced by the high frequency of the words ‘aplikasi’,’bagus’, ’buka’, ‘ok dan ‘bantu’.

The obstacle of this study is that there are users who leave critical comments but give a rating of 4 or 5 so that labeling sentiment based on ratings is still less effective in labeling a review. LSTM and GRU are very suitable for use in big data. So to get deeper into LSTM and GRU you can use large datasets. Future research can also add other methods as comparison material such as the light GBM and FB Profet models.

REFERENCES

Subagja, A. R., Widiastiwi, Y., & Chamidah, N. (2021). Klasifikasi Ulasan Aplikasi Jenius pada Google Play Store Menggunakan Algoritma Naive Bayes. *Informatik : Jurnal Ilmu Komputer*, *17*(3), 197. https://doi.org/10.52958/iftk.v17i3.3652

Kandhro, I. A., Chhajro, M. A., Kumar, K., Lashari, H. N., & Khan, U. (2019). Student Feedback Sentiment Analysis Model Using Various Machine Learning Schemes A Review. *Indian Journal of Science and Technology*, *14*(12), 1–9. https://doi.org/10.17485/ijst/2019/v12i14/143243

Aslam, N., Rustam, F., Lee, E., Washington, P. B., & Ashraf, I. (2022). Sentiment Analysis and Emotion Detection on Cryptocurrency Related Tweets Using Ensemble LSTM-GRU Model. *IEEE Access*, *10*, 39313–39324. https://doi.org/10.1109/ACCESS.2022.3165621

Birjali, M., Kasri, M., & Beni-Hssane, A. (2021). A comprehensive survey on sentiment analysis: Approaches, challenges and trends. *Knowledge-Based Systems*, *226*, 107134. https://doi.org/10.1016/j.knosys.2021.107134

Chlap, P., Min, H., Vandenberg, N., Dowling, J., Holloway, L., & Haworth, A. (2021). A review of medical image data augmentation techniques for deep learning applications. *Journal of Medical Imaging and Radiation Oncology*, *65*(5), 545–563. https://doi.org/10.1111/1754-9485.13261

Doloksaribu, H. P., & Samuel, Y. T. (2022). Komparasi Algoritma Data Mining Untuk Analisis Sentimen Aplikasi Pedulilindungi. *Jurnal Teknologi Informasi: Jurnal Keilmuan Dan Aplikasi Bidang Teknik Informatika*, *16*(1), 1–11. https://doi.org/https://doi.org/10.47111/jti.v16i1.3747

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

Hidayat, R., & Mustawinar, B. H. (2022). Pemodelan Jumlah Wisatawan Dengan Autoregressive Integrated Moving Average Dan Recurrent Artificial Neural Network. *Mathline : Jurnal Matematika Dan Pendidikan Matematika*, *7*(1), 53–65. https://doi.org/10.31943/mathline.v7i1.262

Illia, F., Eugenia, M. P., Rutba, S. A., Stis, P. S., Otto, J., No, I., & Jakarta, E. (2021). Sentiment Analysis on PeduliLindungi Application Using TextBlob and VADER Library. *Proceedings of 2021 International Conference on Data Science and Official Statistics (ICDSOS)*, *64*, 278–288. https://doi.org/https://doi.org/10.34123/icdsos.v2021i1.236

Imanuddin, S. H., Adi, K., & Gernowo, R. (2023). Sentiment Analysis on Satusehat Application Using Support Vector Machine Method. *Journal of Electronics, Electromedical Engineering, and Medical Informatics*, *5*(3), 143–149. https://doi.org/https://doi.org/10.35882/jeemi.v5i3.304

Kemenkes. (2023). *Besok PeduliLindungi Resmi Bertransformasi Menjadi SATUSEHAT Mobile*. https://sehatnegeriku.kemkes.go.id/baca/rilis-media/20230228/2042474/besok-pedulilindungi-resmi-bertransformasi-menjadi-satusehat-mobile/

Muhammad, P. F., Kusumaningrum, R., & Wibowo, A. (2021). Sentiment Analysis Using Word2vec and Long Short-Term Memory (LSTM) for Indonesian Hotel Reviews. *Procedia Computer Science*, *179*(2020), 728–735. https://doi.org/10.1016/j.procs.2021.01.061

Mustopa, A., Hermanto, Anna, Pratama, E. B., Hendini, A., & Risdiansyah, D. (2020). Analysis of user reviews for the pedulilindungi application on google play using the support vector machine and naive bayes algorithm based on particle swarm optimization. *2020 5th International Conference on Informatics and Computing, ICIC 2020*, *19*, 1–7. https://doi.org/10.1109/ICIC50835.2020.9288655

Nurrohmat, M. A., & SN, A. (2019). Sentiment Analysis of Novel Review Using Long Short-Term Memory Method. *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, *13*(3), 209–218. https://doi.org/10.22146/ijccs.41236

Rahmad, F., Suryanto, Y., & Ramli, K. (2020b). Performance Comparison of Anti-Spam Technology Using Confusion Matrix Classification. *IOP Conference Series: Materials Science and Engineering*, *879*(1), 1–11. https://doi.org/10.1088/1757-899X/879/1/012076

Santur, Y. (2019). Sentiment analysis based on gated recurrent unit. *2019 International Conference on Artificial Intelligence and Data Processing Symposium, IDAP 2019*, 1–5. https://doi.org/10.1109/IDAP.2019.8875985

Shahid, F., Zameer, A., & Muneeb, M. (2020). Predictions for COVID-19 with deep learning models of LSTM, GRU and Bi-LSTM. *Chaos, Solitons and Fractals*, *140*, 110212. https://doi.org/10.1016/j.chaos.2020.110212

Soni, M., Barot, Y., & Gomathi, S. (2020). A review on Privacy-Preserving Data Preprocessing. *Journal of Cybersecurity and Information Management*, *5*(2), 16–30. https://doi.org/10.54216/jcim.040202

Yadav, A., & Vishwakarma, D. K. (2020). Sentiment analysis using deep learning architectures: a review. *Artificial Intelligence Review*, *53*(6), 4335–4385. https://doi.org/10.1007/s10462-019-09794-5

Yu Y, Si X, Hu C, Z. J. (2019). A Review of Reccurent Neural Networks: LSTM Cells and Network Architectures. *Neural Computation*, *31(7)*, 1235–1270. https://doi.org/10.1162/neco_a_01199