

# Sentiment Analysis On Twitter Posts About The Russia and Ukraine War With Long Short-Term Memory

Allwin M. Simarmata<sup>1)\*</sup>, Anthony<sup>2)</sup>, Tiffany<sup>3)</sup>, Matthew Evan Phanie<sup>4)</sup>

<sup>1,2,3,4)</sup> Universitas Prima Indonesia, Indonesia

<sup>1)</sup>[allwinsimarmata@unprimdn.ac.id](mailto:allwinsimarmata@unprimdn.ac.id), <sup>2)</sup>[anthonyxu1211@gmail.com](mailto:anthonyxu1211@gmail.com), <sup>3)</sup>[tiffany2001siaucen@gmail.com](mailto:tiffany2001siaucen@gmail.com),

<sup>4)</sup>[matthewep01@gmail.com](mailto:matthewep01@gmail.com)

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**Abstract:** Sentiment analysis is one method for evaluating public opinion from the received text. In this study, we evaluate the performance of the LSTM model with Sastrawi in sentiment analysis in Indonesian using a Twitter dataset totaling 2537 data collected regarding the Russo-Ukrainian war. The purpose of this study is to determine the reliability of the LSTM model with Sastrawi in sentiment analysis in Indonesian and to evaluate the performance of the model with the collected Twitter dataset regarding the Russian-Ukrainian war. The method used in this study is data pre-processing, training and validation of the LSTM model with Literature, and model evaluation using the metrics of accuracy, precision, recall, and F1 score. In the dataset collected in this study, positive, neutral and negative sentiments were 54.7%, 35% and 10.2%. The results obtained from this study indicate that the LSTM model with Literature can provide good results in sentiment analysis with a prediction accuracy of 82%. The implication of the results of this study is that the LSTM model with Sastrawi can be used for sentiment analysis on Twitter and further research needs to be carried out with a wider and more diverse dataset, especially to produce even better accuracy.

**Keywords:** Twitter Sentiment analysis, Long Short Term Memory, Russia Ukraine War, Natural Language Processing.

## INTRODUCTION

The Russia-Ukraine conflict is a conflict that began between Russia and Ukraine in 2014 and escalated in 2022. The conflict started after pro-Russian President Viktor Yanukovich was overthrown from power in Ukraine. Russia then acknowledged and supported the pro-Russian rebellion in the northeastern region of Ukraine, leading to clashes between pro-Russian forces and Ukrainian security forces. The conflict also led to tensions between Russia and several Western countries, especially the European Union and the United States (Shevtsov et al., 2022). Sentiment analysis research can be useful in analyzing the sentiments or emotions contained in texts, such as social media posts or internet comments.

In relation to the Russia-Ukraine conflict, sentiment analysis research can be used to analyze how people view this event through the writings they make on the internet (Melnik, Galina et al., 2019; Shevtsov et al., 2022). Military threats can also be detected, as shown in research by Melnik et al., which shows that media outside of Russia spread negative news about Russia that incites hatred towards Russia (Melnik, Galina et al., 2019).

In this research, the author will examine the sentiment analysis of the 2022 Russo-Ukrainian War. Several Natural Language Processing (NLP) models that are widely researched for sentiment analysis include the Robustly Optimized BERT Pre-training Approach (RoBERTa) (Xiaolong et al., 2021),

\*[Anthonyxu1211@gmail.com](mailto:Anthonyxu1211@gmail.com)



Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA)(Siino et al., 2022), and Sastrawi(Siswanto & Dani, 2021). Sastrawi is used for text processing tasks, text analysis, and text classification. However, what sets Sastrawi apart from other NLP models is its focus on changing Indonesian words to their base form in a text, so the author will use the Sastrawi method in this research(Siswanto & Dani, 2021).

Regarding machine learning algorithms to predict sentiment, there are several algorithms that have performed well in sentiment prediction on Twitter data, such as Cat Boost Classifier (Patil & Loksha, 2022), Convolutional Neural Network (CNN) (Rai et al., 2020), and Long Short-term Memory (LSTM) (U. D. Gandhi et al., 2021; Rai et al., 2020; Wazery et al., 2018a). The LSTM algorithm has been used to achieve good results in various tasks, including language translation, language modeling, and speech recognition. In previous studies, the LSTM algorithm has proven to be superior to other models, so the author will use the LSTM algorithm in this research.

## LITERATURE REVIEW

In a previous study by Elshakankery and Ahmed, a Hybrid model combining Lexicon-based and Support Vector Machine (SVM) was used on an Arabic language dataset. The model proved to be superior by up to 17.55% compared to other models that only used lexicon or SVM(ELSHAKANKERY & AHMED, 2019). This research is innovative in terms of the dataset, which is in Indonesian language and was obtained using Web Scraper and processed using Sastrawi. In addition, since previous studies(U. Gandhi et al., 2021; Wazery et al., 2018b) have shown that the LSTM algorithm is superior to other models, the author will use this algorithm in this research.

## METHOD

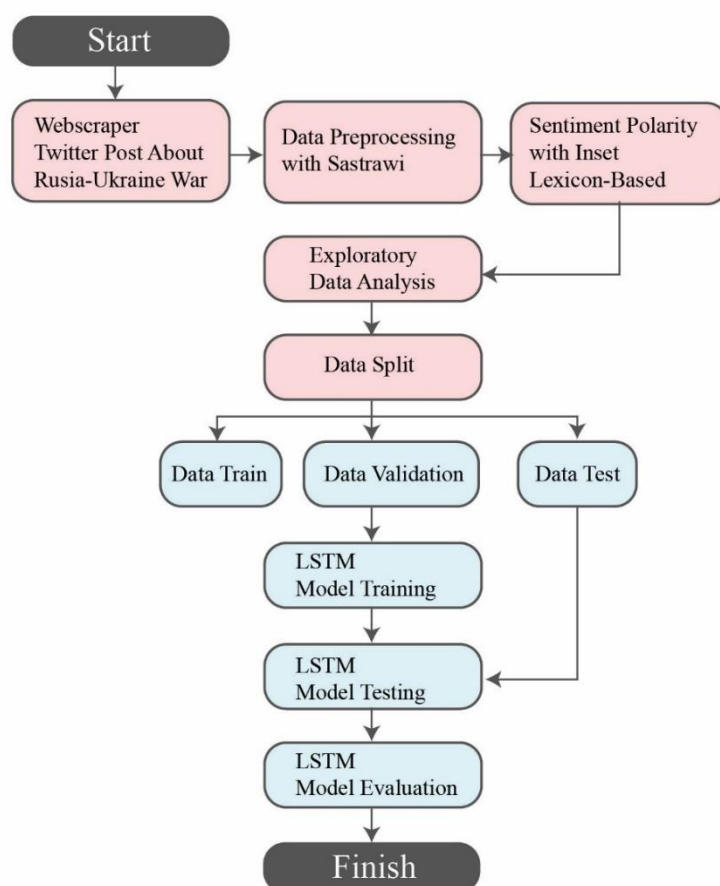


Figure 1. Research Procedure

\*[Anthonyxu1211@gmail.com](mailto:Anthonyxu1211@gmail.com)

### Data Collection

The research collected a dataset of 2,537 Twitter posts related to the Russia-Ukraine War using the free service of webscraper.io. The dataset was obtained by inputting various keywords, including 'Russia Ukraine War', 'Russia Ukraine Conflict', 'Russia Ukraine', and 'Putin Zelenskyy', which were shared from January 7, 2023 to January 14, 2023.

### Webscraper Twitter

This research uses Webscraper to collect Twitter datasets about the Russia-Ukraine War. Webscraper will navigate the Twitter site and search for tweets using related keywords. Important information such as tweet text, poster, and time will be taken and stored. This data will be analyzed to understand public opinion, the spread of misinformation, and the influence of certain groups or individuals. This study uses the free service of Webscraper.io, which can be easily used (Coombs, 2021).

### Stemming process for the Indonesian language using Sastrawi

Sastrawi is a Python library for performing stemming in the Indonesian language. Stemming reduces words to their basic form which have the same meaning. This is important for pre-processing text data in NLP. Sastrawi uses the Nazief and Adriani algorithm which removes suffixes at the end of a word according to certain rules (Siswanto & Dani, 2021).

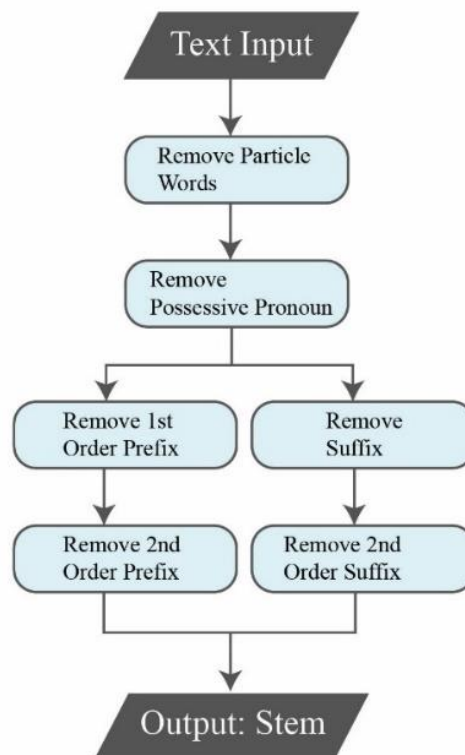
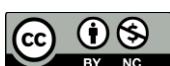


Figure 2. Stemming Process

### InSet Lexicon-based Sentiment Polarity.

InSet is a method for evaluating sentiment in Indonesian text using a Lexicon-based dictionary shared by Koto and Rahmanyngtyas, which was previously used to study Microblogs sentiment (Koto & Rahmanyngtyas, 2017). An example of its implementation can be seen in the previous image. However, this method has limitations because word interpretation depends on the context in which the word appears. For example, the word "very" can have different interpretations and give negative or positive sentiment, depending on the context. Deep Learning models such as LSTM can predict sentiment more accurately because they learn context and make predictions based on patterns in the text. This model is useful in sentiment analysis of product reviews, tweets, and social media posts.

\*[Anthonyxu1211@gmail.com](mailto:Anthonyxu1211@gmail.com)



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Figure 3. Example of Lexicon-based Process in Indonesian Language

### Long Short Term Memory

LSTM (Long Short-term Memory) algorithm was chosen to predict sentiment because the Lexicon-based method has limitations in understanding context. LSTM is a type of recurrent neural network that can learn sequence dependencies in prediction problems with sequences. The way it works includes a Forget Gate to decide the long-term memory status, a New Memory Network and Input Gate to determine new information to be entered into the memory, and an Output Gate to produce a new hidden layer (Wazery et al., 2018b).

## RESULTS

### The Result of Twitter Webscraper for the Russia-Ukraine War

Web scraping is the process of extracting data from websites to be processed and stored for analytical purposes. Webscraper.io is one of the web scraping platforms that allows you to extract data from websites without having in-depth programming knowledge. Here is the process of web scraping using Webscraper.io to extract a dataset of tweets about the Russia-Ukraine war:

1. Open Webscraper.io and create a "Scraper."
2. Determine the URL of the website that you want to crawl.
3. Create a "Selector" to determine the portion of the web page from which you want to extract data.
4. Determine the columns you want to extract and save them in CSV format.
5. Run the "Scraper" and wait for the web scraping process to finish.

After successfully collecting the data in CSV format, it needs to be imported into Jupyter Notebook using the Pandas library. First, import the Pandas library as shown in the following image:

```
tweets = pd.read_csv('../dataset_perang_rusia_ukraina.csv')
tweets
```

	author_id	author_name	author_username	created_at	edit_history_tweet_ids	tweet_id
0	1.530000e+18	Amone Boj	amone_boj	2023-01-14 09:01:09+00:00	[1614185843773554689]	1.610000e+18
1	1.530000e+18	Amone Boj	amone_boj	2023-01-13 12:07:29+00:00	[1613870345454522368]	1.610000e+18
2	2.269822e+09	Eduardo Jonathan	eduardojonath15	2023-01-14 08:52:03+00:00	[1614183551293083650]	1.610000e+18
3	1.600000e+18	Kopi Manis	kopimanisyo	2023-01-14 08:11:46+00:00	[1614173415249772546]	1.610000e+18
4	1.600000e+18	Kopi Manis	kopimanisyo	2023-01-13 08:11:29+00:00	[1613810954956947456]	1.610000e+18
...	...	...	...	...	...	...
2532	5.099870e+08	Phares Elisha	PharesElisha1	2023-01-07 15:19:53+00:00	[1611744438581334016]	1.611740e+18
2533	4.955444e+08	Maluka Khamis	MalukaKhamis	2023-01-07 12:52:42+00:00	[1611707399987134465]	1.611710e+18
2534	7.540470e+17	capitalis	ganafmargi	2023-01-07 12:51:46+00:00	[1611707161486438402]	1.611710e+18
2535	1.471030e+18	kuatbaca.com	kuatbacacom	2023-01-07 12:47:21+00:00	[1611706052508278784]	1.611710e+18
2536	9.661431e+08	S Huda Agatha	shda_agatha_	2023-01-07 11:24:56+00:00	[1611685309900787716]	1.611690e+18

Figure 4. Webscraper Result

\*[Anthonyxu1211@gmail.com](mailto:Anthonyxu1211@gmail.com)



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The Twitter text can be viewed by calling 'text' as shown in the following image.

```
tweets.text

0      Invasi Rusia Ukraina Hari 322, Kota Soledar Uk...
1      Invasi Rusia Ukraina Hari 322, Kota Soledar Uk...
2      @tptrvasia @TVRINasional @btvidofficial 2. Feb...
3      Google Alert - Perang Rusia-Ukraina - https://...
4      Google Alert - Perang Rusia-Ukraina - https://...
...
2532   Vita itaisha pale majeshi ya Russia yatatoka U...
2533   @Davidngonde @FatmahShokat Hapana. Niliacha ku...
2534   @bdleonanda @Gugus29502671 Suka ga suka, zelen...
2535   Dari senapan sampe HIMARS, sobbb.. gak sia2 #Z...
2536   @Dew0W1snu Ini masih belum seberapa, yg parah ...
Name: text, Length: 2537, dtype: object
```

Figure 5. The result of the data imported into the Jupyter Notebook file

### Result of Data Pre-processing using Sastrawi

Sastrawi is a Python library used for stemming in the Indonesian language. Stemming is the process of transforming words in a text into their base form (or root word) by removing affixes. This is important in sentiment analysis because different words but with the same meaning are often used in the text. For example, the words "damai" and "damainya" have the same meaning but are different in suffixes, with stemming, both words can be transformed into the base word "damai" making it easier to count in sentiment analysis process(Siswanto & Dani, 2021).

```
tweets.text

0      Invasi Rusia Ukraina Hari 322, Kota Soledar Uk...
1      Invasi Rusia Ukraina Hari 322, Kota Soledar Uk...
2      @tptrvasia @TVRINasional @btvidofficial 2. Feb...
3      Google Alert - Perang Rusia-Ukraina - https://...
4      Google Alert - Perang Rusia-Ukraina - https://...
...
2532   Vita itaisha pale majeshi ya Russia yatatoka U...
2533   @Davidngonde @FatmahShokat Hapana. Niliacha ku...
2534   @bdleonanda @Gugus29502671 Suka ga suka, zelen...
2535   Dari senapan sampe HIMARS, sobbb.. gak sia2 #Z...
2536   @Dew0W1snu Ini masih belum seberapa, yg parah ...
Name: text, Length: 2537, dtype: object

Sastrawi

tweets.text_preprocessed

0      [invasi, rusia, ukraina, kota, soledar, ukrain...
1      [februari, perang, rusiaukraina, Kamis, februari]
2      [google, alert, perang, rusiaukraina]
3      [perang, rusia, ukraina, lanjut, masyarakat, s...
4      [wick, tolol, org, bahas, rusia, ukraina, suru...
...
1510   [vita, itaisha, pale, majeshi, ya, russia, yat...
1511   [hapana, niliacha, kufuatilia, muda, tu, kaka,...
1512   [suka, ga, suka, zelensky, kuat, ya, posisi, p...
1513   [senapan, sampe, himars, sobbb, gak, sia, as, ...
1514   [yg, parah, kemarin, yg, pas, kongres, ngasih,...
Name: text_preprocessed, Length: 1515, dtype: object
```

Figure 6. Result of Data Preprocessing using Sastrawi

### InSet Lexicon-based Sentiment Polarity

As explained in Chapter 2, sentiment polarization with the InSet Lexicon-based Sentiment Polarity method is used to determine sentiment before being used to train the LSTM algorithm in this research.

\*[Anthonyxu1211@gmail.com](mailto:Anthonyxu1211@gmail.com)



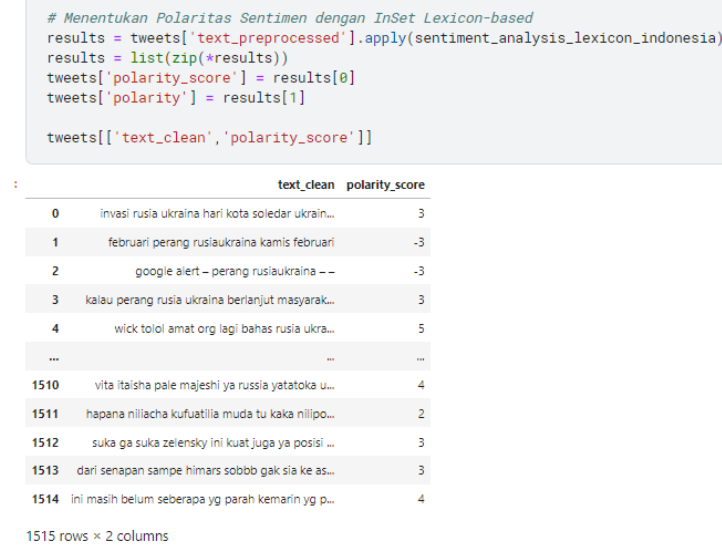


Figure 7. Result of Data Preprocessing using InSet Lexicon-based

### Exploratory Data Analysis (EDA)

After the dataset is successfully imported, Exploratory Data Analysis (EDA) can be observed. First, the number of data can be observed as shown in the following image. It can be seen that the amount of data generated is quite large even though the data was collected only within a week.

```
# Melakukan EDA terkait jumlah dan tanggal pengumpulan data
print('Jumlah data:')
print(len(tweets))
print('Dataset dikumpulkan dari tanggal:')
print(tweets.created_at.min())
print('Hingga tanggal:')
print(tweets.created_at.max())
```

Jumlah data:  
1515  
Dataset dikumpulkan dari tanggal:  
2023-01-07 08:41:53+00:00  
Hingga tanggal:  
2023-01-14 10:12:46+00:00

Figure 8. The Amount of Data Collected

Secondly, the polarity ratio generated by InSet in the previous stage can be analyzed using a pie chart with the help of Matplotlib. The result can be seen in the following image, it can be seen that the highest ratio is positive at 54.7%. Meanwhile, negative sentiment is only 10.2%.

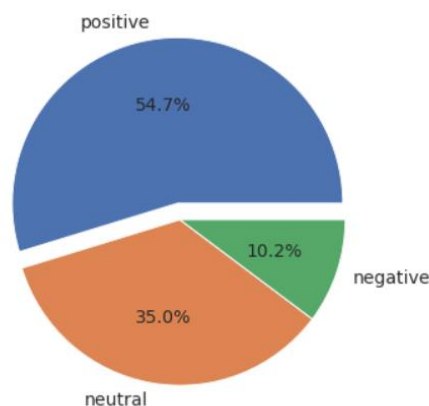


Figure 9. The Sentiment Polarity Ratio of the Studied Dataset

\*[Anthonyxu1211@gmail.com](mailto:Anthonyxu1211@gmail.com)



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Finally, with the help of the WordCloud library, we can see the topics that are often discussed by the public regarding the Russia-Ukraine war as shown in the following image.



Figure 10. Frequently Occurring Words in the Dataset

### Split Data

The next step in this research is the Data Split stage which divides the dataset into two parts, namely the Testing Data which is 20% and the Training Data which is 80%. There is also Validation Data that takes 10% of the Training Data.

### Training Model

As explained in Chapter 2, the LSTM model can be combined with Lexicon-based to improve the accuracy of the model and reduce errors from Lexicon-based. The initial step is the training process. This process involves providing Train and Validation data to the model and asking the model to make predictions. Generally, there are three types of training results that can be produced, namely Underfitted, Overfitted, and Good Fit/Robust. The good result is the Good Fit/Robust, as shown in the following figure.



Figure 11. Example of Good and Bad Training Results

Then, to see whether the model studied in this research produces good or bad results, the model will make predictions based on the data it receives and compare them to the actual results. Then, the model will be improved by adjusting its weights and parameters to make better predictions. This process is repeated until the model achieves the desired level of performance, which takes 25 training steps as shown in the following figure. It can be seen that the training process in this study is not strictly vertical like the Underfitted example in the previous figure, but rather tends to be upward simultaneously like the Good Fit/Robust example. However, there is a problem of ups and downs that only occurred once at Epoch 13, so the problem of Overfitting is not too severe as shown in the previous figure.

\*[Anthonyxu1211@gmail.com](mailto:Anthonyxu1211@gmail.com)

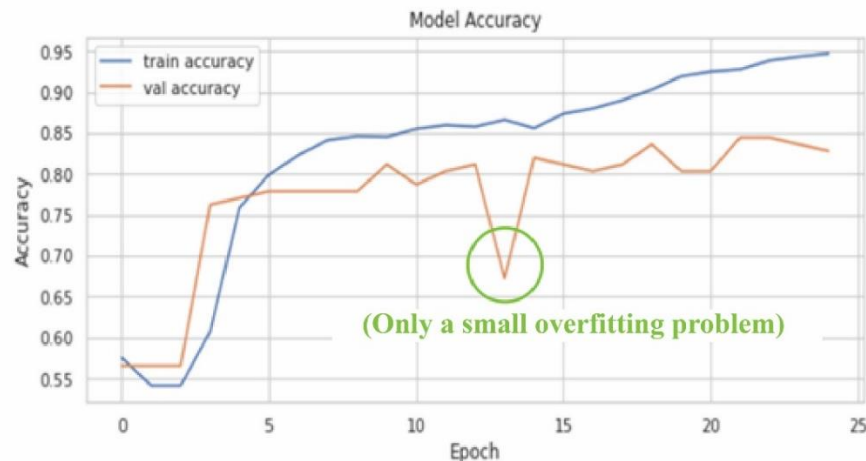


Figure 12. Report on Performance of LSTM Training Process

### Model Evaluation

In the prediction output with 3 sentiment classes (Positive, Neutral, Negative), the Confusion Matrix consists of a 3x3 matrix. The matrix rows represent the actual classes, while the matrix columns represent the classes predicted by the model. The evaluation of the Confusion Matrix using the Testing Data can be seen in the following image. It can be seen that there were 2 correct predictions for negative sentiment, 87 correct predictions for neutral sentiment, and 160 correct predictions for positive sentiment. The rest are the incorrect predictions made by the LSTM model.

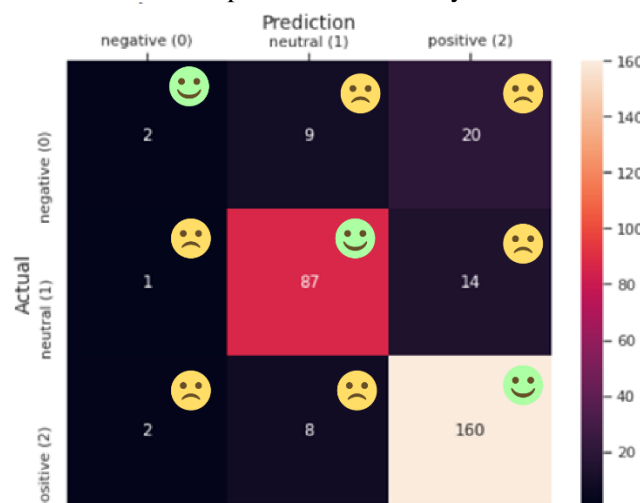


Figure 13. Tabel Confusion Matrix Data Testing LSTM

With the Confusion Matrix above, we can determine the proportion of correct predictions out of the total predictions. It can be calculated as follows:

$$Accuracy = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100\% = \frac{(2+87+160)}{303} \times 100\% = 82\% \quad (3.1)$$

### DISCUSSIONS

The results obtained from the training and validation process in the form of a hybrid model combining InSet Lexicon-based and LSTM can provide good results in sentiment analysis. This can be seen from the accuracy values obtained in the training and validation process, where the average training and validation accuracy values reached above 75% and the highest value even up to 95%. The majority of the training results show that both values are not significantly different, so it can be concluded that the model does not experience overfitting.

\*[Anthonyxu1211@gmail.com](mailto:Anthonyxu1211@gmail.com)



## CONCLUSION

Conclusion of this research is that LSTM model with Sastrawi and Indonesian Twitter dataset collected in this study can provide good results in sentiment analysis with a prediction accuracy of 82%. This indicates that LSTM algorithm can be relied upon for sentiment analysis and can be used to understand public opinion on the Russia-Ukraine war. However, this research only used a limited dataset and the accuracy achieved can still be improved. Therefore, further research is needed to prove the reliability of the LSTM algorithm on Twitter datasets related to the Russia-Ukraine war, to evaluate the model with different datasets, and to improve its performance.

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