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Sentiment Analysis of Trending Topics on Social Media X Using Natural Language Processing and LSTM

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ABSTRACT

In today's fast-paced digital era, trending news on Social Media X spreads rapidly, influences public opinion, and is often vulnerable to disinformation. This study analyzes netizens' sentiment towards trending topics on Social Media X using Natural Language Processing (NLP) and a Long Short-Term Memory (LSTM) model. A dataset of 4483 comments was collected across 15 trending topics (Feb–Jun 2025). The preprocessing steps included cleansing, case folding, stopword removal, tokenization, and translation to handle bilingual data. Results show sentiment distribution: 35% positive, 36% negative, and 29% neutral. Model performance varied between 34%–67% accuracy, with precision, recall, and F1-scores indicating that topic sensitivity, language diversity, and data imbalance strongly influenced outcomes. This research contributes to text analytics by providing a baseline model for real-time trending news sentiment analysis in Indonesia, particularly under multilingual and noisy data conditions.

I. INTRODUCTION

Trending news on social media X has a very significant social impact due to its rapid virality, its ability to influence the spread of misinformation. In a matter of minutes, an issue can reach millions of users, shape public opinion, and even real action in the offline world. This phenomenon makes analyzing public sentiment not just an academic activity but also a practical need for the government, media, and society to understand the developing direction, for example, political, social, and cultural issues that become trending topics often cause sharp polarization in the digital space, so that it can increase conflict of opinion, decrease the quality of information, and the rise of misinformation and disinformation [1] .

Understanding public sentiment toward trending news is crucial for several reasons. First, it can help detect social polarization and the level of public acceptance of a particular policy or issue. Second, sentiment analysis can form the basis for more responsible journalism, where the media not only reports a phenomenon but also considers how the public responds to it [2]. Third, from a practical perspective, mapping public sentiment can support more adaptive decision-making by policymakers, companies, and civil society organizations [3].

According to data from DataReportal (2025), the number of active users of platform X in Indonesia reached more than 25.4 million users, an increase of approximately 8.2% compared to the previous year. Globally, this platform has more than 550 million monthly active users, making it a key medium for shaping public opinion. This increase in user participation strengthens the role of social media as a digital public discussion arena. Although much previous research has addressed sentiment on social media, most have focused on a single issue for a limited period of time. Few studies have examined the dynamics of public sentiment in real time on multilingual trending issues. This represents a major research gap.

Previous studies on social media analysis have generally focused on static or long-term issues, such as government policies, elections, and digital service evaluations [4]. However, such research has not fully addressed the challenges of trending issues, which are dynamic, temporary, and highly contextual. Viral topics are typically ephemeral and full of mixed language, requiring a more adaptive technical approach. Therefore, this study emphasizes sentiment analysis, trending news that is dynamic and rapidly changing in nature, to provide a more up-to-date understanding of public perception.

Trending news often triggers various public responses, whether in the form of support, criticism, or debate that takes place in the digital space, besides that it also makes it easier to analyze public opinion [5]. As previous research conducted previously that discussed free meals which had become a hot topic on social media where users often post their opinions on various issues, including free meal programs, which makes it a rich source of data for sentiment analysis. By using NLP methods, we can collect and analyze data from these platforms to gain insight into public perception of the program [6]. From this research, how the results of all trending topic news from February to June were analyzed and presented as a comparison, from which news had the most positive, negative, and neutral sentiment.

This research lies in the application of a combination of Natural Language Processing (NLP) and Long Short-Term Memory (LSTM) algorithms to analyze sentiment in multilingual and real-time social media data [7]. Sentiment analysis is the process of understanding, processing text data to obtain information in an opinion sentence whether it tends to have a positive or negative opinion [8]. Using NLP allows computers to extract meaning from unstructured text [9]. Meanwhile, LSTM is able to model long-term context in sentences so that it can recognize complex emotional patterns [10]. With this approach, the research is expected to be able to provide a more in-depth picture of how public opinion is formed and developed around trending issues in Indonesia.

Thus, this research attempts to fill this gap by utilizing a combination of NLP and LSTM to analyze public perceptions of various trending issues in an adaptive, contextual, and sustainable manner.

II. Methods

This research method uses preprocessing, namely NLP (Natural Language Processing) and model creation using LSTM (Long Short-term Memory) [11]. This research method is used based on journals as references and ideas for the creation of this research, with a journal entitled 'Analysis of Public Sentiment towards Terrorists in Twitter Social Media using NLP' written by Shobrina Fathoniah, Chaerur Rozikin in 2022. In this process begins by first taking data and trending topics. Data collection through scraping 15 trending topics, resulting in 4483 comments using the python programming language using the tweepy library to access API X and retrieve tweets based on trending keywords. After being obtained, the data is collected and stored, after which it will be processed according to the stages of the method. Which stages include the following figure 1.

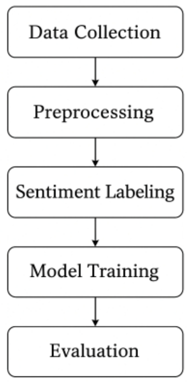

Figure 1. Research methods

A. Data Collection

This process begins by first collecting trending data and topics. Data collection was done by scraping 15 trending topics, resulting in 4,483 comments using the Python programming language using the tweepy library to access API X and retrieve tweets based on trending keywords. The data obtained includes the tweet text content, upload time, user ID, number of likes, retweets, and replies [12]. This process aims to collect raw data that reflects real-time public opinion on trending issues in Indonesia, including political, social, and environmental topics.

B. Preprocesing

In the Preprocessing process, it will be done using NLP. Data preprocessing aims to transform raw data into a format used for analysis, the stages of data preprocessing include combining data from several sources, cleaning data to remove duplicate observations and noise, and selecting relevant records and features in data mining [13]. In the process of cleaning HTML text using BeautifulSoup, in addition to removing URLs, Mentions, and emoticons using emoji, re, and Contraction. In this process, punctuation, menshion, emoji, and even unused links will be removed. Before carrying out the deletion process, a translation process is added to make it easier to obtain sentiment results. Using depp_translator to translate the text. The text must first be translated into English considering that textblob is only able to label English text [14]. After carrying out the translation process, the preprocessing process is carried out. After cleaning, the tokenization process will be carried out to cut words [15]. After carrying out this process, the textBlob library can be used to obtain sentiment results. In sentiment results, if the data produces -1, it produces negative results, if it produces 0, it is neutral, and if 1, it is positive.*Sentiment Labeling.*

After the cleaning process, automatic sentiment labeling can be performed using the textBlob library to obtain sentiment results. In the sentiment results, if the data yields -1, it's negative, if it yields 0, it's neutral, and if it yields 1, it's positive. Automatically label thousands of tweets quickly and consistently without the need for manual labeling.

C. Model training

In the classification of model creation, the dataset is divided into two, namely training data and testing data [16]. The resulting data will form an accuracy and loss graph that has carried out the model training process with a different number of steps.

D. Evaluation

After modeling is carried out, the model analysis process is continued, which will result in a comparison of accuracy, precision, and recall values between each topic [17].

III. RESULT AND DISCUSSION

A. Data Collection

In carrying out the data collection process, the author has conducted research on trending topics to be studied where the data was obtained from the social media platform X using scraping. Scraping is done automatically using the Pytho programming language [18]. Data was taken on February 1, 2025 to June 30, 2025 using keywords according to things that are trending on social media X. After conducting research on what things are trending or things that are often discussed on social media X, the results obtained were 15 trending topics that will be research data, although not all things or trending topics were included, but the topics were selected that were suitable to be research material.

TABLE I
LIST OF TRENDING TOPICS, TRENDING DATES AND KEYWORDS

Trending Topics	Trending Date/ Most Talked	Keywords
#Carmen	03-Feb-25	carmen
#Kaburajadulu	11-Feb-25	kabur aja dulu
#IndonesiaGelap	17-Feb-25	indonesia gelap
#KorupsiPertamina	25-Feb-25	korupsi pertamina
#PertamaxOplosan	26-Feb-25	pertamax oplosan
#RUUTNI	15-Mar-25	RUU TNI
#Bromo	18-Mar-25	ganja di bromo
#Ijazah Palsu	15-Apr-25	ijazah palsu
#DediMulyadi	18-Apr-25	dedi mulyadi
#BarakMiliter	01-May-25	barak militer
#JucsticeForArgo	27-May-25	jucstice for argo
#SaveRajaAmpat	05-Jun-25	save raja ampat
#AlGhazali	14-Jun-25	al ghazali
#IranvsIsrael	17-Jun-25	iran
#Rinjani	25-Jun-25	rinjani

After collecting the data, the next step is importing the dataset for processing. To import the data, upload it to Google Colab, which serves as a medium for data input and processing.

```
import pandas as pd
```

```
from google.colab import drive
drive.mount('/content/drive')

Mounted at /content/drive
```

```
df1 = pd.read_csv('/content/drive/My Drive/Dataset/RUU_TNI.csv')
df1
```

Figure 2. *Import Dataset*

From the image, when the data has been collected and entered into Google Colab to facilitate sentiment data processing. In importing data is done one by one per topic, after which the NLP (Natural Language Processing) process and LSTM (Long Short-Term Memory) Model analysis are immediately carried out. Because in the NLP process and LSTM Model Analysis each topic has the same process, it will be done one by one by starting with importing the data that has been collected, then the NLP process is carried out, then the LSTM Model Analysis is carried out. After the first topic has obtained results, then the next data is imported to be processed until all topics have final results.

B. Prepocessing

In the data processing process using NLP (Natural Language Processing), several steps are carried out to obtain sentiment analysis results in the form of Positive, Negative, and Neutral results for each comment from the data obtained. The sentiment results will then be further processed to obtain the analysis results of the LSTM algorithm model as the final result of several trending topics that have been obtained.

In conducting sentiment analysis, TextBlob will use to determine whether the data sentiment results are positive, negative, or neutral. This is because the data obtained is mostly in Indonesian, and some foreign languages will be converted to English. Because TextBlob will only respond to text in English, therefore, before proceeding with the process, sentiment Using the TextBlob library is recommended for translation into English. During the translation process, unnecessary columns are removed from each data item, leaving only full_text and user_id_str. Before translation, the deep_translator package is first installed using the pip install deep_translator command. Once successfully installed, the GoogleTranslator module is imported for use as an automatic translator.

Before tokenization, the text contains several punctuation marks and emojis that need to be cleaned. The cleansing process removes noise in the form of emoticons and less important characters from the review sentence so that the text can be tokenized, or separated into individual words [19].

```
!pip install contractions
!pip install emoji
```

```
import emoji
import contractions
import re
```

```
def cleansing(df1):
  t1 = re.sub('RT\s','',df1)

  t2 = re.sub('\B@\w+','',t1)

  t3 = emoji.demojize(t2)

  t4 = re.sub('(http|https):\/\/\S+','',t3)

  t5 = re.sub('#+','',t4)

  t6= t5.lower()

  t7 = re.sub(r'(.)\1+',r'\1\1', t6)

  t8 = re.sub(r'[\?\.\!]+(?=[\?.\!])','',t7)

  t9 = re.sub(r'[^a-zA-Z]', ' ', t8)

  t10 = contractions.fix(t9)

  return t10
```

```
for i, r in df1.iterrows():
  y = cleansing(r['full_text_en'])
  df1.loc[i, 'full_text_en'] = y
```

```
df1.to_csv('/content/drive/My Drive/Dataset/RUUTNI_tokenn.csv')
```

```
df1 = pd.read_csv('/content/drive/My Drive/Dataset/RUUTNI_tokenn.csv')
df1
```

Figure 3. Cleansing process

The cleansing process involves data cleansing of text using Python with the help of the emoji, contractions, and re (regular expression) libraries. The cleansing(df1) function is designed to clean text in several steps, including removing retweets (RT), mentions (@user), URLs, and hashtags (#), converting emojis to text, lowering letters to lowercase, removing excessive punctuation, and simplifying repeated letters. The function then corrects English abbreviations using contractions.fix().

Tokenization involves separating individual words in the text. Tokenization is the process of breaking a sentence into word fragments [20]. The tokenization process was carried out on July 12, 2025, involving tokenization, stopword removal, and part-of-speech (POS) tagging using the NLTK library. First, NLTK resources such as punkt, stopwords, and wordnet, which are needed for text processing, were installed and downloaded. Next, the pos_dict dictionary was created to map POS categories into the format WordNet (adjectives, verbs, nouns, adverbs). The token_stop_pos(text) function is then used to break the text into tokens with word_tokenize, removing stopwords, and assigning POS labels to each word according to its category. After that, the full_text_en column in the DataFrame is filled with empty strings to replace NaN values, then the POS tagging function is applied to produce a new column named POS_tagged which contains word pairs and their respective POS labels.

C. Sentiment Labeling

After tokenization, the TextBlob library can be used to obtain sentiment results from the text. This not only yields sentiment results but also Subjectivity and Polarity results. Subjectivity results indicate whether the text is opinionated or objective. To determine whether the text is opinionated or objective or factual, a result of 0 indicates objective or factual; a result of 1 indicates opinionated or factual. Unlike subjectivity, Polarity is a number that determines whether the text is positive, negative, or neutral. A score of -1 indicates negative, a score of 0 indicates neutral, and a score of 1 indicates positive.

	full_text_en	user_id_str	POS_tagged	Subjectivity	Polarity	TextBlob
0	the plenary session of the ratification of the...	1371650588	[(plenary, a), (session, n), (ratification, n)...	0.000000	0.000000	Neutral
1	synergy at the end of the barrel when the hi...	1159689173340585984	[(synergy, n), (end, n), (barrel, n), (hierarc...	0.202222	0.053333	Positive
2	news the government and the indonesian parlia...	1172167188800655360	[(news, n), (government, n), (indonesian, a), ...	0.000000	0.000000	Neutral
3	under the militaristic regime prabowo this con...	1369663239718465538	[(militaristic, a), (regime, n), (prabowo, n),...	0.550000	-0.400000	Negative
4	emergency call the tni bill is quietly ratifi...	978646566	[(emergency, n), (call, v), (tni, n), (bill, n...	0.166667	0.044444	Positive

Figure 4. Sentiment Results Display

The image shows the sentiment results in the TextBlob column. This was done one by one for each topic, resulting in a sentiment analysis for each topic. This sentiment analysis was done one by one because each topic has different text data, which results in different sentiments.

TABLE 2
OVERALL SENTIMENT RESULTS

No	Topics	Results			Total
		Positive	**Negative**	**Neutral**	
1	Carmen	144	18	131	293
2	Kabur Aja Dulu	98	153	46	297
3	Indonesia Gelap	46	201	54	301
4	Korupsi pertamina	88	164	49	301
5	Pertamax oplosan	98	113	90	301
6	RUU TNI	105	120	76	301
7	Bromo	109	62	125	296
8	Ijazah Palsu	68	202	31	301
9	Dedi Mulyadi	165	48	88	301
10	barak militer	80	192	29	301
11	Justice For Argo	167	50	84	301
12	Save Raja Ampat	87	62	152	301
13	Al Ghazali	128	56	114	298
14	Iran vs Israel	81	68	140	289
15	Rinjani	105	103	93	301
	Total :	**1569**	**1612**	**1302**	**4483**

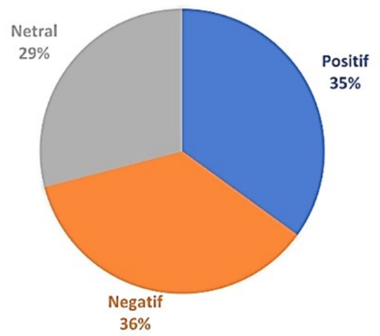

Figure 5. Sentiment Graph Results

The overall sentiment results are 35% positive, 36% negative, and 29% neutral, showing a slightly higher negative tendency in sensitive issues such as corruption (#PertaminaCorruption) and education (#FakeIjazah). In contrast, topics related to officials and celebrities (#DediMulyadi, #AlGhazali) tend to be positive sentiment, while environmental topics (#SaveRajaAmpat) generate higher neutrality. The graph shows the range of 34%-67% for each topic. Topics (#IndonesiaDark) and (#FakeIjazah) show the highest performance at 67%, while (#Rinjani) gets 34%.

D. Model Training

Classification requires model creation. The previously refined dataset is divided into two parts: training data and testing data. Each topic also has different training and testing data. These results create a graph, displaying the accuracy and loss results for training the model with varying numbers of steps, depending on the topic's training results. The following graph compares the accuracy and loss results for each trending topic.

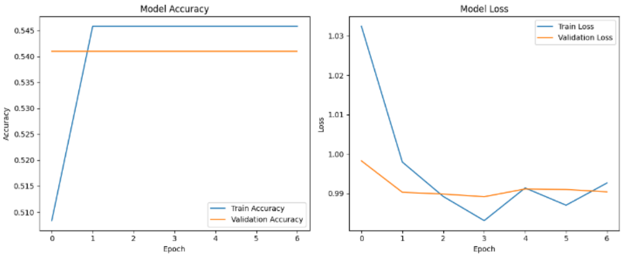

Figure 9. Grafik Akurasi dan Loss #KorupsiPertamina

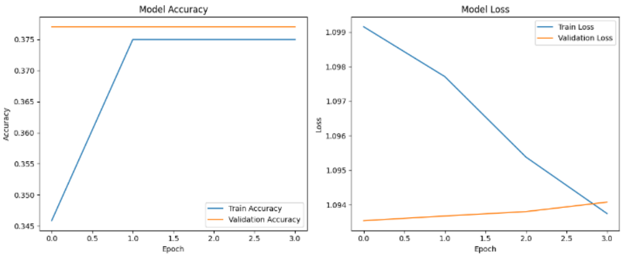

Figure 10. Grafik Akurasi dan Loss #PertamaxOplosan

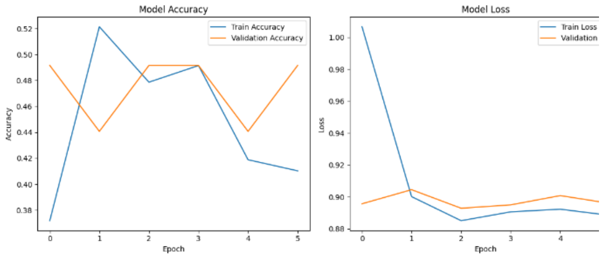

Figure 6. Grafik Akurasi dan Loss #Carmen

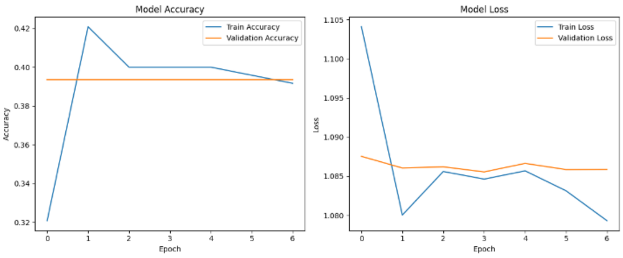

Figure 11. Grafik Akurasi dan Loss #RUUTNI

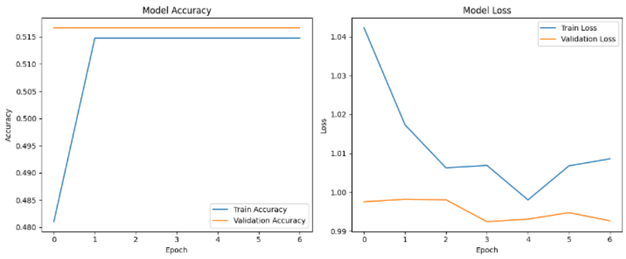

Figure 7. Grafik Akurasi dan Loss #KaburAjaDulu

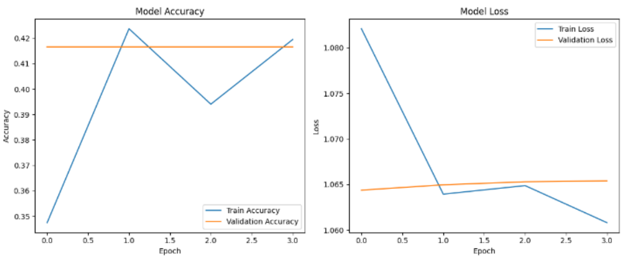

Figure 12. Grafik Akurasi dan Loss #Bromo

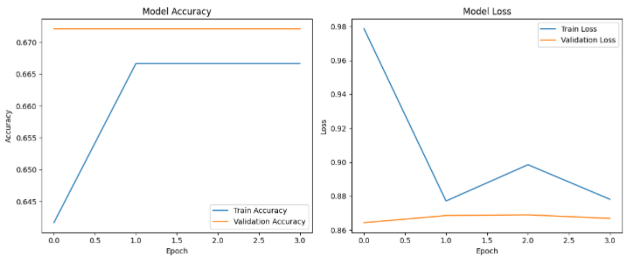

Figure 8. Grafik Akurasi dan Loss #IndonesiaGelap

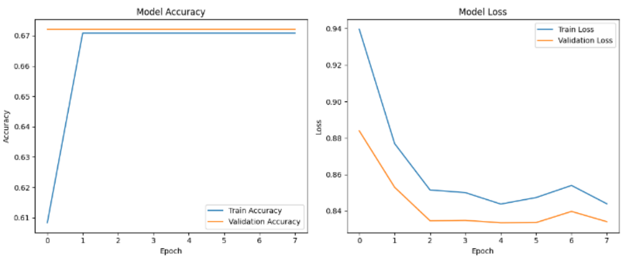

Figure 13. Grafik Akurasi dan Loss #IjazahPalsu

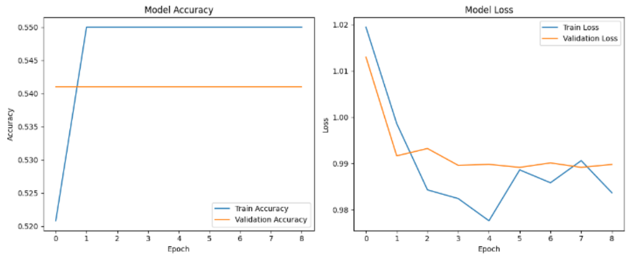

Figure 14. Grafik Akurasi dan Loss #DediMulyadi

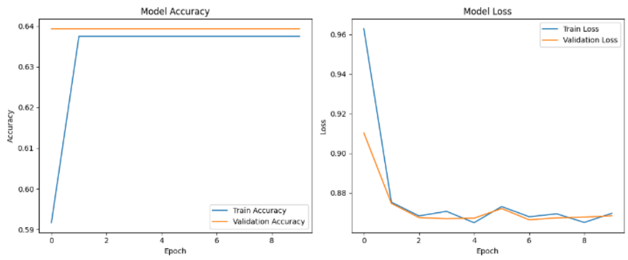

Figure 15. Grafik Akurasi dan Loss #BarakMiliter

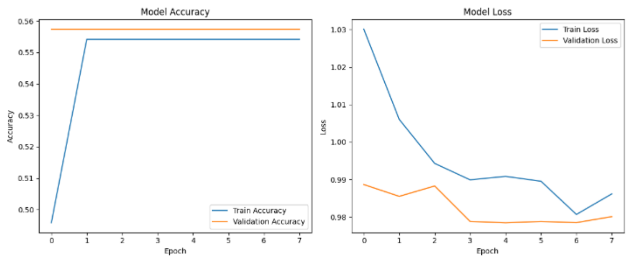

Figure 16. Grafik Akurasi dan Loss #JusticeForArgo

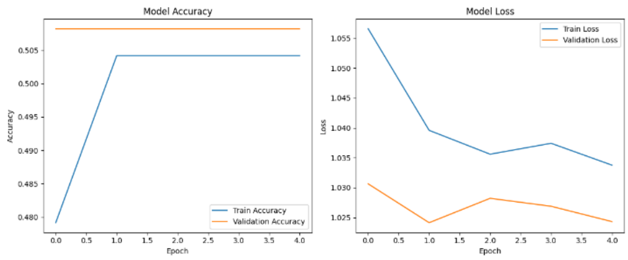

Figure 17. Grafik Akurasi dan Loss #SaveRajaAmpat

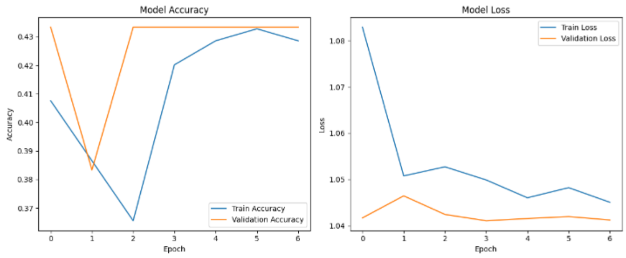

Figure 18. Grafik Akurasi dan Loss #AlGhazali

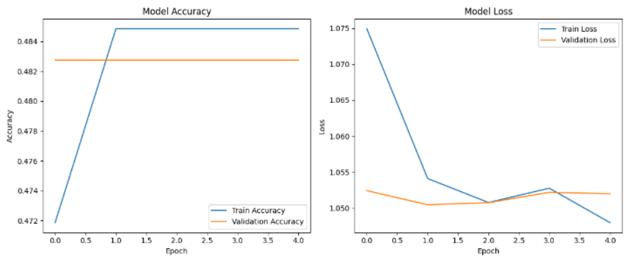

Figure 19. Grafik Akurasi dan Los #IranVSIsrael

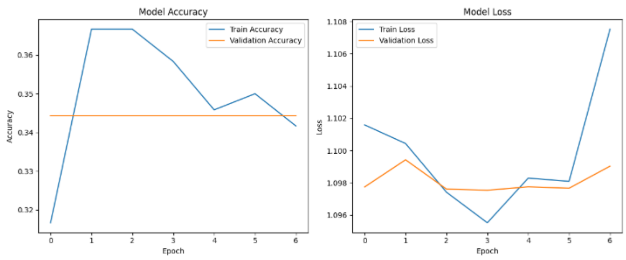

Figure 20. Grafik Akurasi dan Loss # Rinjani

Based on the graph above, it can be seen that several topics have different graph results, adjusting the results from the training data and testing data from various topics. To create the graph, a training model is first created, where the training units are stored and will be used to test the data for each topic later. Accuracy and loss graphs are important tools for evaluating LSTM model performance, monitoring the model learning process, and identifying overfitting or underfitting issues. The research results show that some topics produce fairly accurate models, but others are less successful due to the high data or complexity of public opinion. Accuracy variations between topics are also caused by several factors, including:

TABLE 3
EXPLANATION OF ACCURACY VARIATION ACROSS TOPICS

Topics	Language Charactes	Language Characters	Explanatin
#Rinjani	Lots of slang vocabulary	The model has difficulty	Many use mixed

		capturing emotional meaning	language styles
#IndonesiaGelap	Formal language and ambiguous opinions	Clear and consistent context	Easy model to recognize the polarity of sentences
#Ijazah Palsu	Dominant negative words	Directed and firm sentiment	Makes it easier to learn LSTM models
#SaveRajaAmpat	Lots of informatie sentences dan ajakan positif	Tends to be neutral	Makes it difficult for the model to distinguish between neutral and positive
#RUUTNI	Political debate	Contains ironic language	Needs better handling of sarcasm

This difference in context is what causes variations in accuracy results between topics. The model tends to be more accurate on issues with clear polarity, and less accurate on topics with ambiguous language style.

E. Evaluasi

After creating a graphical model of accuracy and loss using the LSTM algorithm, the results of accuracy, precision, recall, and F1-Score were obtained.

TABLE 4
LSTM TEST RESULTS

Topic	Accuracy	Precision	Recall	F1-Score
Carmen	49%	24%	49%	32%
Kabur Aja Dulu	52%	27%	52%	35%
Indonesia Gelap	67%	45%	67%	54%
Korupsi Pertamina	54%	29%	54%	38%
pertamax oplosan	38%	14%	38%	21%
RUU TNI	39%	15%	39%	22%
bromo	42%	17%	42%	25%
Ijazah Palsu	67%	45%	67%	54%
Dedi Mulyadi	54%	29%	54%	38%
barak militer	64%	41%	64%	50%
Justice For Argo	56%	31%	56%	40%
Save Raja Ampat	51%	26%	51%	34%
wedding al ghazali	43%	19%	43%	26%
iran vs israel	48%	23%	48%	31%
rinjani	34%	12%	34%	18%

The LSTM model achieved accuracy ranging from 34% (#Rinjani) to 67% (#IndonesiaDark, and #IjazahPalsu). Performance varied due to dataset imbalance, topic complexity, and language diversity. Precision and F-1 scores highlighted that the model performed better on controversial topics with clear polarity compared to general or mixed discussions. These findings imply that sentiment analysis on trending news requires handling imbalanced data and accounting for multilingualism. Practically, this research aids media monitoring, while theoretically it provides evidence that LSTM is adaptable for real-time sentiment analysis on dynamic topics.

IV. CONCLUSION

The study successfully applied NLP and LSTM in analyzing the sentiment of netizen comments on trending news on Social Media X, highlighting the impact of data imbalance and multilingual text on model performance. Its contribution lies in establishing a foundation for real-time sentiment analysis on trending topics in Indonesia, with sentiment to combat disinformation, support media responsibility, and advance multilingual text analytics.

REFERENCES

[1] D. Duei Putri, G. F. Nama, and W. E. Sulistiono, “Analisis Sentimen Kinerja Dewan Perwakilan Rakyat (DPR) Pada Twitter Menggunakan Metode Naive Bayes Classifier,” *Jurnal Informatika dan Teknik Elektro Terapan*, vol. 10, no. 1, Jan. 2022, doi: 10.23960/jitet.v10i1.2262.

[2] A. Tirtayasa, A. Listiyo Wibowo, P. DI Jl Panjaitan No, K. Purwokerto Selatan, K. Banyumas, and J. Tengah, “Sentiment Analysis Tweet KTT G-20 di Media Sosial Twitter Menggunakan Metode Naïve Bayes,” 2023. [Online]. Available: https://developer.twitter.com/

[3] T. C. Adisti, E. Daniati, and A. Ristiyawan, “Analisis Sentimen Ujaran Kebencian Pada Tweet Di Twitter,” 2025.

[4] G. Mario Conroy Paridy Man, A. Aristo Jansen Sinlae, and E. Ngaga, “JIP (Jurnal Informatika Polinema) Analisis Sentimen di Media Sosial X tentang IKN dengan Naïve Bayes”.

[5] M. Hamzah, “Penerapan Natural Language Processing (NLP) dalam Analisis Sentimen pada Media Sosial,” *Journal of Informatics and Computer Research (JICR)*, vol. xx, No. xx, 2024, doi: 10.1007/s41060-018-0111-1.

[6] W. Anggriyani and M. Fakhriza, “Analisis Sentimen Program Makan Gratis Pada Media Sosial X Menggunakan Metode NLP,” *Journal of Computer System and Informatics (JoSYC)*, vol. 5, no. 4, pp. 1033–1042, Aug. 2024, doi: 10.47065/josyc.v5i4.5826.

[7] M. Wildan Agba, P. Eosina, and D. Primasari, “Memanfaatkan Analisis Sentimen Twitter untuk Mengelola Reputasi Merek: Studi Kasus Skincare Merek X Menggunakan Support Vector Machine”, doi: 10.38035/jim.v4i3.

[8] T. Elizabeth, “Analisis Sentimen Ulasan Aplikasi PrimaKu Menggunakan Metode Support Vector Machine,” *Jurnal Teknik Informatika dan Sistem Informasi*, vol. 9, no. 4, 2022, [Online]. Available: http://jurnal.mdp.ac.id

[9] N. Suarna and W. Prihartono, “Penerapan NLP (Natural Language Processing) Dalam Analisis Sentimen Pengguna Telegram Di Playstore,” 2024.

[10] L. M. Azizah, D. B. Ajipratama, N. A. R. Putri, and C. Damarjati, “Analisa Sentimen Masyarakat Terhadap Kebijakan Vaksinasi Covid-19 Di Indonesia Pada Twitter Menggunakan Algoritma LSTM La,” *JURNAL IPTEKKOM Jurnal Ilmu Pengetahuan & Teknologi Informasi*, vol. 24, no. 2, pp. 161–172, Dec. 2022, doi: 10.17933/iptekkom.24.2.2022.161-172.

[11] S. Fathoniah and C. Rozikin, “Analisis Sentimen Masyarakat terhadap Teroris dalam Media Sosial Twitter menggunakan NLP,” *Jurnal Ilmiah Wahana Pendidikan*, vol. 2022, no. 13, pp. 412–419, doi: 10.5281/zenodo.6962682.

[12] R. Luthfiansyah Dan, B. Wasito, S. Program, and I. Sistem, “Analisis Sentimen Terhadap Para Kandidat Presiden 2024

Berdasarkan Netizen Pengguna Twitter Dengan Metode Data Mining Dan Text Mining."

[13] A. Berrajaa, "Natural Language Processing for the Analysis Sentiment using a LSTM Model." [Online]. Available: www.ijacsa.thesai.org

[14] A. Mukti, A. D. Hadiyanti, A. Nurlaela, and J. Panjaitan, "Sistem Analisa Sentiment Bakal Calon Presiden 2024 Menggunakan Metode NLP Berbasis Web The Sentiment Analysis System For the 2024 Presidential Candidates Uses Web-Based NLP Method," 2023.

[15] J. R. Jim, M. A. R. Talukder, P. Malakar, M. M. Kabir, K. Nur, and M. F. Mridha, "Recent advancements and challenges of NLP-based sentiment analysis: A state-of-the-art review," *Natural Language Processing Journal*, vol. 6, p. 100059, Mar. 2024, doi: 10.1016/j.nlp.2024.100059.

[16] D. Duei Putri, G. F. Nama, and W. E. Sulistiono, "Analisis Sentimen Kinerja Dewan Perwakilan Rakyat (DPR) Pada Twitter Menggunakan Metode Naive Bayes Classifier," *Jurnal Informatika dan Teknik Elektro Terapan*, vol. 10, no. 1, Jan. 2022, doi: 10.23960/jitet.v10i1.2262.

[17] A. Rolangon *et al.*, "Perbandingan Algoritma LSTM Untuk Analisis Sentimen Pengguna Twitter Terhadap Layanan Rumah Sakit Saat Pandemi Covid-19 The Comparison of LSTM Algorithms for Twitter User Sentiment Analysis on Hospital Services During the Covid-19 Pandemic."

[18] M. Puspa Indah *et al.*, "Analisis Jaringan Informasi Dalam Natural Language Processing Terhadap Situs Cnn Indonesia Menggunakan Graphgpt (Studi Kasus: Berita Hasil Pilpres 2024) Program Studi Sistem Informasi Fakultas Sains Teknologi Universitas Bina Darma Palembang)," 2024.

[19] F. Fakhri Irfani and M. Triyanto, "Analisis Sentimen Review Aplikasi Ruangguru Menggunakan Algoritma Support Vector Machine."

[20] M. I. Fikri, T. S. Sabrila, Y. Azhar, and U. M. Malang, "Perbandingan Metode Naïve Bayes dan Support Vector Machine pada Analisis Sentimen Twitter".