

# Exploring Sentiment Trends: Deep Learning Analysis of Social Media Reviews on Google Play Store by Netizens

Rosa Eliviani<sup>1</sup>, Dwi Diana Wazaumi<sup>2</sup>

<sup>1,2</sup>Informatics Management Study Program, Astra Polytechnic, Indonesia

## Article Info

### Article history:

Received Mar 08, 2024

Revised Mar 19, 2024

Accepted Mar 29, 2024

### Keywords:

Instagram

App reviews

Sentiment analysis

LSTM

Social media

## ABSTRACT

This study explores sentiment analysis of Instagram app reviews using Long Short-Term Memory (LSTM) algorithms. The rise of app stores has transformed digital interactions, particularly for social media apps. Leveraging LSTM, we aim to understand user sentiments expressed in Instagram application reviews, offering insights to enhance user experience and address concerns. The methodology involves data crawling, preprocessing, LSTM model training, and evaluation metrics. Our findings reveal promising results in accurately identifying user sentiments, with an accuracy of 77.77%, precision of 0.45, recall of 0.089, and F1-score of 0.15. This study underscores the importance of sentiment analysis in understanding user feedback and its implications for app development and user engagement.

*This is an open access article under the [CC BY-SA](#) license.*



## Corresponding Author:

Rosa Eliviani,

Informatics Management Study Program,

Astra Polytechnic,

Sungai Bambu, Kec. Tj. Priok, North Jakarta, Special Capital Region of Jakarta 14330

Email: [rosa.eliviani@polytechnic.astra.ac.id](mailto:rosa.eliviani@polytechnic.astra.ac.id), [reliviani@gmail.com](mailto:reliviani@gmail.com)

## 1. INTRODUCTION

The rise of app stores has become a hallmark of contemporary digital life, particularly within the realm of mobile platforms dominated by Apple's App Store for iOS and Google Play for Android. While extensive empirical studies have scrutinized the properties of individual apps, scant attention has been paid to the stores themselves, despite their pivotal role in software distribution and their influence on development practices [1]. However, [1] also reveal considerable operational variability among app stores, challenging the applicability of existing research findings across the spectrum of store types. Using the rapid development of applications on increasingly numerous app stores, one of the rapidly growing ones today is social media applications. With the advancement of smartphone technology and 4G internet network, people are connecting with each other. Social media has become a part of today's life, people easily obtain information with just one click [2]. Even not only for sharing photos randomly, social media nowadays become one of the tools in business. Social media accounts can serve as a platform to communicate with potential buyers. Sellers can announce newly opened businesses, market products for sale, promote and expand customer reach, so that customers can also share their experiences when buying and provide feedback. All of this happens quickly, allowing businesses to respond to build customer trust by responding to positive feedback given up to addressing negative customer feedback [3].

There are many social media platforms used by people nowadays, such as Facebook, Instagram, Twitter, Whatsapp, etc. One of them is Instagram, which was created in San Francisco by Kevin Systrom and Mike Krieger. This application has become a website that provides a platform for sharing photos. The origin of the name Instagram stems from blending the terms "instant camera" and "telegram", which now has features that continue to grow and is popular among people [3]. Currently, Instagram has also become one of the social media platforms utilized as a commercial enterprise. Users on Instagram have accounts as their identities, enabling them to interact with posts from other accounts by commenting, sharing, or liking [4]. People can download various social media applications from the Google Play Store, including the Instagram app. Moreover, people can also provide their ratings and reviews on the Google Play Store. These ratings range from one to five. Based on these rating scores and text reviews, we can gauge the emotions of the application users as well as the reviewers.

The identification of emotions has become a compelling subject of interest among researchers due to its importance in psychology, social dynamics, and business. Individuals communicate their emotions through a variety of means, including facial expressions, verbal and written language, and behavior. Emotion detection tools offer a crucial and effective method for identifying and classifying emotional states across different applications. Artificial intelligence (AI) is frequently employed in this process. Machine learning and deep learning algorithms can generate accurate solutions for detecting emotional disorders among users of social media platforms. Numerous research studies and survey articles have explored emotion detection utilizing textual data [5].

Previous research has been closely related to this topic. One of them is in the study [6] on analyzing the sentiment of netizen comments on Instagram social media accounts with the naive Bayes classification model. Then for Google Play applications, several studies have been conducted such as in [7] which examines the characteristics of sports apps, themes highlighted by users of sports apps in their ratings and reviews, and the most common complaints about sports apps. There are also studies that look at the app market aspect such as [8] which examines the implications of Google's policy change on local Korean markets, particularly on the app store market, which includes local app stores that have a minor yet significant presence. Furthermore, due to the existence of text reviews and ratings in Google app reviews, there is research that examines novel framework for predicting contradictions in Google App numeric reviews and ratings using Deep Learning approaches [9]. Then there is research that performs sentiment analysis, such as sentiment analysis for hotel reviews using Aspect-Based Sentiment Analysis (ABSA) methodology [10], an aspect-level sentiment classification approach incorporating collaborative extraction hierarchical attention network [11], and sentiment analysis of campus teaching 2 regarding the implementation of Merdeka Belajar Kampus Merdeka utilizing naive Bayes and Euclidean distance methods [12]. However, many use LSTM in their sentiment analysis such as [13], [14], [15], [16], [17], [18], and [19]. In the study [20] several algorithms were compared and LSTM was chosen for its prediction stage.

The ever-expanding user base of Instagram highlights the growing significance of understanding user sentiments conveyed through feedback and reviews on the Instagram app. This research delves into sentiment analysis utilizing Long-short Term Memory (LSTM) algorithms to uncover the underlying sentiments expressed in Instagram app reviews. By examining the sentiments of users towards the app, valuable insights can be gained to enhance user experience and address any concerns or issues. This introduction provides a comprehensive overview of the research, including the background, problem statement, relevant literature, proposed approach utilizing neural network algorithms, and the innovative value of the research in advancing sentiment analysis methodologies.

## 2. RESEARCH METHOD

The methodology employed in this research commences with a comprehensive literature review, as delineated in the introduction subsection. Subsequently, building upon the insights gleaned from the literature review, the research methodology is meticulously crafted, guided by the schematic representation depicted in Figure 1. This methodological framework encompasses three pivotal stages: the dataset stage, training stage, and evaluation stage.

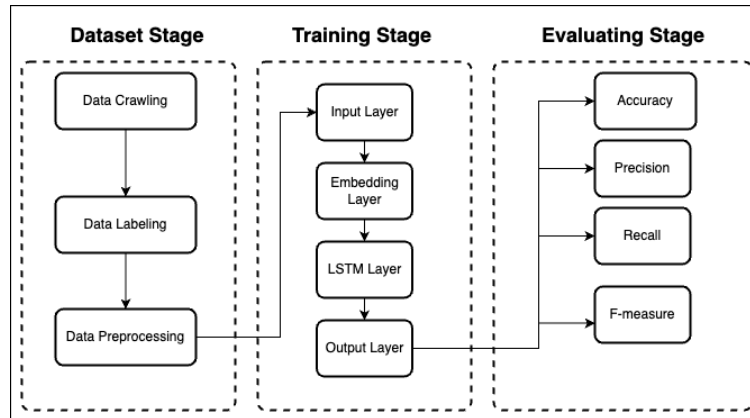


Figure 1. Research Method

The dataset stage involves the systematic acquisition and preparation of the requisite data, where various processes such as data crawling, labeling, and preprocessing are meticulously executed to maintain the reliability and trustworthiness of the dataset. In this stage, the data sources, including Instagram app reviews, are carefully collected, ensuring representativeness and quality. Preprocessing techniques such as tokenization, and handling of noise are applied to clean and prepare the data for analysis. Following this, the training stage ensues, wherein the Long Short-Term Memory (LSTM) algorithm, renowned for its efficacy in handling long-term dependencies, is employed. LSTM, being a category of Recurrent Neural Network (RNN), is adept at retaining information across extended sequences, thereby surmounting challenges associated with vanishing gradients often encountered in traditional RNNs. In this stage, detailed insights into the LSTM model architecture are provided, including the number of layers and units, activation functions, and any regularization techniques employed to prevent overfitting. Hyperparameters tuning, such as learning rate and batch size, are meticulously adjusted to optimize the model's performance. This stage is crucial as it involves the iterative training of the model using the prepared dataset to optimize its parameters and enhance its predictive capabilities.

Finally, the evaluation stage serves as the culmination of the methodology, wherein the trained model is rigorously evaluated to assess its performance. Various performance evaluation metrics like accuracy, precision, recall, and F1-Score are utilized to assess the effectiveness of the model. sentiment analysis model developed using LSTM. A deeper interpretation of these metrics is provided, discussing their significance in the context of sentiment analysis and comparing the results with existing studies or benchmarks in the field. This meticulous evaluation process ensures ensuring the reliability and validity of the findings contributes to the robustness of the research outcomes.

### 3. RESULTS AND DISCUSSION

In this section, we explain the research that we have conducted. Some sub-chapter topics of the results and discussions include dataset, dataset preprocessing, and the machine learning algorithms used. We present some of the results in the form of figures and tables. The following are the results and discussions of this research.

#### 3.1. Dataset

The data crawling process involved leveraging web APIs, particularly those enabling communication from a web server to a browser, and highlighting the broad applicability of the term API, which encompasses various contexts beyond internet-based interactions. Web APIs are commonly utilized by developers accessing well-publicized and documented public services, such as ESPN for athlete details and game scores, and Google for language translations, analytics, and geolocation [21]. Therefore, to obtain the dataset for this research, we utilized the Google data scraper.

In order to gather this data, it is imperative to conduct a review of user feedback on an online investment application available on the Google Play Store. This process involves analyzing user

reviews to categorize them as either positive or negative, enabling the assessment and comparison of accuracy across various online investment applications [22]. The APIs offered by Google-Play-Scraper allow effortless crawling of the Google Play Store for Python, eliminating the need for external dependencies. Specifically, we gathered a dataset based on Instagram social media application reviews and ratings from the Google Play Store, consisting of 1500 reviews filtered by the English language and sorted by relevance. During the data preprocessing stage, several steps were undertaken to clean and prepare the data for analysis. This included text normalization to ensure consistency in language usage, tokenization to break down text into individual words or phrases, and handling noise or outliers to remove irrelevant or misleading data points. Additionally, any duplicate entries or irrelevant information were filtered out to enhance the dataset's quality and reliability for subsequent analysis.

	content	score	at	Year	Month	Day
293	It started cutting out the audio for the video...	1	2023-12-14 03:20:49	2023	12	14
344	This app is horrible. There are SO MANY ADS. A...	1	2023-12-14 04:33:21	2023	12	14
277	Just use Ad-Block at this point. Videos over 4...	1	2023-12-15 18:22:21	2023	12	15
317	3 main extreme irritating things, first, when ...	2	2023-12-15 21:10:05	2023	12	15
343	Play lists should be just songs, not filled wi...	1	2023-12-16 04:51:21	2023	12	16
...	...	...	...	...	...	...
19	Picture in Picture isn't working anymore. I di...	1	2024-02-29 12:42:19	2024	2	29
18	Even when I actually have good Wi-Fi, YouTube ...	1	2024-02-29 12:55:44	2024	2	29
68	PLZ FIX THE APP CRASHES!!! I CAN'T DO ANYTHING...	2	2024-02-29 13:52:46	2024	2	29
392	The latest update has been such a headache! I'...	1	2024-02-29 14:00:08	2024	2	29
124	Every time when I try making a video from my X...	2	2024-03-01 02:26:55	2024	3	1

Figure 2. Dataset

### 3.2. Preprocessing Dataset

Data preprocessing involves performing various operations on data before extracting information and values, as well as after data ingestion, to enhance data quality and make it suitable for use by algorithms. These operations, categorized in different ways as shown in Figure 1, the goal is to attain different data quality attributes like precision, objectivity, comprehensiveness, and traceability [23].

1. Select Required Columns Only: The first step in preprocessing involves selecting the columns (attributes) that are relevant to the analysis or model. This typically includes the review text and any additional metadata that may provide context or valuable information.
2. Select only Positive and Negative Reviews: To focus on sentiment analysis, it is essential to filter the dataset to include only the reviews labeled as positive and negative. Neutral or other categories are excluded to streamline the analysis and ensure clarity in sentiment interpretation.

	content	score	Year	Month	Day	sentiment
0	Great app, easy to use. Facing a little troubl...	4	2020	6	10	positive
1	Overall, I dig the app. But in my Instagram Di...	2	2020	9	21	negative
2	I can't deal with this anymore. When I delete ...	1	2021	8	10	negative
3	Whilst I have had no issue with the app in the...	3	2023	5	19	neutral
4	I have 2 accounts. I operate them simultaneous...	3	2023	8	14	neutral

Figure 3. Sentiment Dataset

3. Attribute and Labels: Defining attributes (features) and labels (target variable) is crucial for building a sentiment analysis model. Attributes usually include the review text, while labels represent the sentiment expressed in the text (positive/negative). This step establishes the groundwork for training and evaluating the model.

4. **Train Test Split:** In order to assess the sentiment analysis model's performance, the dataset undergoes division into training and testing sets. The training set is employed for model training, while the testing set is utilized to evaluate its effectiveness on new and unseen data. This ensures that the model generalizes well to new data.
5. **Getting required labels only and encoding:** Extracting the required sentiment labels from the dataset and encoding them into numerical values is necessary for modeling. For example, sentiments such as "positive" and "negative" can be encoded as numerical values (e.g., 1 and -1, respectively). This encoding facilitates the training of machine learning models.

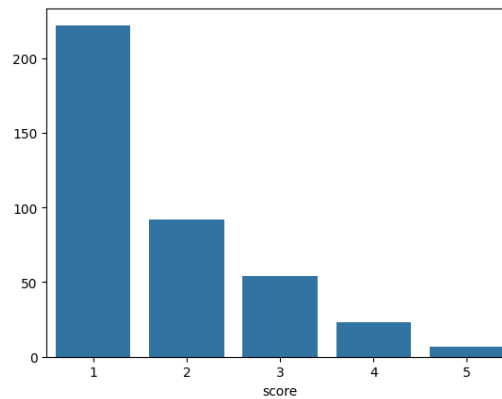


Figure 4. The distribution of review scores

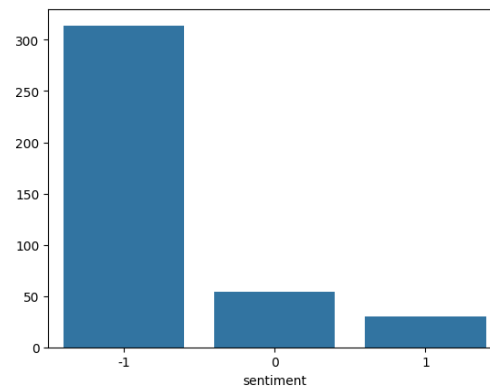


Figure 5. The distribution of review sentiment

6. **Vectorizing a text corpus** involves converting each text into a sequence of integers as handling noise, a crucial step in natural language processing tasks like text classification and sentiment analysis. This process enables machine learning algorithms to process textual data effectively by representing words as numerical values. Through techniques like tokenization and mapping words to integers, we transform a text corpus into a structured numerical format, facilitating the training and prediction processes in various natural language processing tasks.

	content	score	Year	Month	Day	sentiment	content_token
13432	great app easy to use facing a little troubl...	4	2020	6	10	positive	[great, app, easy, to, use, facing, a, little, ...
14180	overall i dig the app but in my instagram di...	2	2020	9	21	negative	[overall, i, dig, the, app, but, in, my, insta...
13242	i can deal with this anymore when i delete a...	1	2021	8	10	negative	[i, can, deal, with, this, anymore, when, i, d...

Figure 6. Vectorizing a text

7. Padding and storing converted sequences play a vital role in preparing textual data for deep learning models in natural language processing (NLP). These sequences, initially converted from text to integers, often vary in length. However, many deep learning models require fixed-length inputs. Padding adds zeros to ensure uniform sequence lengths, facilitating streamlined data processing during training and inference. Additionally, storing these sequences allows for efficient data management. Overall, these preprocessing steps are essential for effectively utilizing textual data in deep learning-based NLP applications.

### 3.3. Training

After the data has been preprocessed, the next stage is the training phase. Training is conducted using Long Short-Term Memory (LSTM), a specific type of Recurrent Neural Network (RNN) known for its proficiency in managing long-term dependencies. LSTM surpasses traditional RNNs by incorporating specialized mechanisms to retain information across extended sequences, thus overcoming issues such as vanishing gradients. While both RNN and LSTM exhibit a chain-like structure, LSTM distinguishes itself by employing multiple gates to precisely regulate the flow of information within each node. LSTM and its variations have showcased significant advantages in addressing problems associated with Long-Term Dependencies (LTED) [5].

The LSTM model architecture comprises several layers tailored to the task of sentiment analysis. Firstly, an embedding layer is utilized, followed by a spatial dropout layer, an LSTM layer, a dropout layer, and finally a dense layer. The embedding layer has an input dimension of `vocab_size` and an output dimension of `embedding_vector_length`. The LSTM layer, crucial for capturing sequential dependencies, consists of 50 units. To prevent overfitting, a dropout rate of 0.5 and a recurrent dropout rate of 0.5 are applied. Additionally, a dropout layer with a dropout rate of 0.2 is incorporated after the LSTM layer. The dense layer, responsible for generating the final sentiment prediction, utilizes the sigmoid activation function. The model is compiled with binary cross-entropy loss and optimized using the Adam optimizer. The model was trained using the `model.fit` function, which takes the padded sequences of training data (`padded_sequence_train`) and their corresponding review labels (`review_labels_train[0]`) as inputs. To monitor the model's performance, a validation split of 20% was specified. The model underwent training for 5 epochs with a batch size of 32, effectively optimizing its parameters to enhance its performance in sentiment analysis.

### 3.4. Evaluating

This sentiment analysis study emphasizes the critical role sentiment plays in human communication, which is often reflected in various forms such as comments on social media platforms, articles, and feedback [24]. Neural networks, including LSTM, are among the methods utilized for sentiment analysis. The evaluation of sentiment analysis models typically involves quantitative metrics such as accuracy, precision, recall, and F1-score, which are calculated based on the values of true positive (tp), true negative (tn), false positive (fp), and false negative (fn).

Accuracy measures the proportion of correctly identified instances among all instances identified. It's important to note that while accuracy can be high with low precision, aiming for both high accuracy and high precision ensures consistently precise results [25]. Precision quantifies the proportion of correct instances among all retrieved instances, while recall measures the proportion of correct instances among all correct instances.

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn}$$

In the context of sentiment analysis, accuracy indicates how well the model correctly identifies sentiments overall. Precision assesses the reliability of the model in correctly identifying positive and negative sentiments, while recall measures the model's ability to capture all instances of positive and negative sentiments accurately.

$$Precision = \frac{tp}{tp + fp}$$

$$Recall = \frac{tp}{tp + fn}$$

The F1-score, being the harmonic mean of precision and recall, provides a balanced measure of the model's performance. It's crucial to interpret these metrics together as they complement each other. A high F1-score indicates both high precision and recall, suggesting a well-performing sentiment analysis model.

$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Strengths of these metrics include their ability to provide quantitative measures of model performance, enabling comparison across different models or datasets. However, their limitations lie in their inability to capture nuances in sentiment analysis, such as sarcasm or ambiguity. In this study, the reported accuracy, precision, recall, and F1-score are 0.7777, 0.45, 0.089, and 0.15, respectively. These metrics indicate a moderate level of performance in sentiment analysis. Comparing these results with existing studies or benchmarks in the field would provide further insights into the model's efficacy.

### 3.5. Discussion of Results

The sentiment analysis conducted on Instagram app reviews provides valuable insights into user sentiments expressed within the platform. By analyzing the collected data, several key themes and patterns emerge, shedding light on users' experiences and perceptions of the Instagram application. One of the predominant themes identified in the reviews is user experience. Many users express their satisfaction with the app's user interface, features, and overall usability. Positive sentiments often revolve around seamless navigation, engaging content, and the convenience of interacting with the platform. Conversely, negative sentiments are also prevalent, particularly concerning technical issues and bugs. Numerous reviews highlight frustrations with app crashes, glitches, and performance issues, which adversely affect the user experience. These negative experiences often lead to dissatisfaction and may prompt users to voice their concerns publicly.

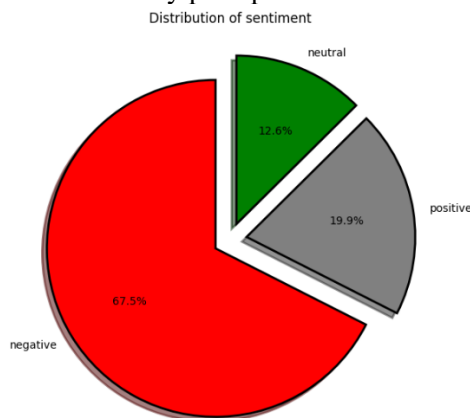


Figure 7. Distribution of sentiment

Additionally, users frequently express their opinions on desired features or improvements they hope to see in future updates. These suggestions provide valuable feedback to app developers, offering insights into user preferences and areas for enhancement to maintain user satisfaction and retention. In the Figure 7, the distribution of sentiments across the reviews varies, with negative sentiments generally outweighing positive ones. However, it's crucial to note that neutral sentiments also exist, representing users providing factual information without expressing strong opinions or sentiments. While analyzing the results, it's essential to address outliers or discrepancies that may impact the accuracy of the sentiment analysis. Extreme sentiments, inconsistencies between

expressed sentiments and predicted ones, and potential biases in the dataset are factors to consider when interpreting the findings.

Overall, this comprehensive analysis of Instagram app reviews offers valuable insights for app developers and marketers. By understanding user sentiments, identifying common pain points, and prioritizing feature enhancements, developers can enhance the app's functionality, address user concerns, and ultimately improve the overall user experience on the platform.

#### 4. CONCLUSION

In conclusion, this study underscores the efficacy of LSTM algorithms in analyzing sentiments within Instagram app reviews. The insights gleaned from this analysis offer valuable opportunities to enhance user experience and mitigate concerns. Moreover, the study underscores the pivotal role of sentiment analysis in informing app development and user engagement strategies. Future research avenues may explore the broader application of sentiment analysis across diverse social media platforms, elucidating its impact on user behavior and app performance. Additionally, ongoing advancements in deep learning techniques present promising avenues for refining sentiment analysis models, augmenting their accuracy, and bolstering their applicability in real-world contexts. Despite demonstrating the utility of LSTM algorithms in sentiment analysis, this study acknowledges inherent limitations such as dataset biases and constraints in generalizability to other social media platforms. Subsequent research endeavors may delve into alternative deep learning architectures, integrate domain-specific features, and conduct qualitative analyses to deepen understanding. Leveraging insights from sentiment analysis can catalyze enhancements in the Instagram user experience. Strategically prioritizing feature enhancements and addressing technical issues based on user feedback can amplify user engagement. Tailoring marketing strategies to user sentiments holds the potential to further drive engagement, while continuous monitoring facilitates adaptive product development, ensuring sustained relevance and competitiveness in the market.

#### REFERENCES

- [1] W. Zhu, S. Proksch, D. M. German, M. W. Godfrey, L. Li e S. McIntosh, "What is an app store? The software engineering perspective," *Springer: Empirical Software Engineering*, 2 January 2024.
- [2] S. A. Salam e R. Gupta, "Emotion Detection and Recognition from Text using Machine Learning," em *International Journal of Computer Sciences and Engineering*, Indore, India, 2018.
- [3] D. K. Sharma e A. K. Rai, "Impact of Social Media network by VIKOR MCDM Method," em *International Conference on Cognitive Computing and Engineering Education (ICCCCEE)*, India, 2023.
- [4] H. Teotia, G. Shishodia, E. Tyagi, A. Prakash e S. Avasthi, "Instagram Analysis and Activity Automation: Using Python and Selenium Automation Tools," em *International Conference on Computational Intelligence, Communication Technology and Networking (CICTN)*, India, 2023.
- [5] A. A. Maruf, F. Khanam, M. M. Haque, Z. M. Jiyad, M. F. Mridha e Z. Aung, "Challenges and Opportunities of Text-Based Emotion Detection: A Survey," *IEEE Access*, vol. 12, pp. 18416-18450, 2024.
- [6] A. Anggara, S. Widiono, A. T. Hidayat e Sutarman, "Analysis of Netizen Comments Sentiment on Public Official Statements on Instagram Social Media Accounts," *International Journal of Advances in Data and Information Systems*, vol. 3, n° 2, pp. 87-97, 2022.
- [7] B. Chembakottu, H. Li e F. Khomh, "A large-scale exploratory study of android sports apps in the google play store," *Information and Software Technology*, vol. 164, pp. 1-18, 2023.
- [8] S. Hwang e S. Kim, "Google's app store policy change and the responses elicited from mobile content firms: A case study on Korea's app store ecosystem," *Telematics and Informatics*, vol. 72, pp. 1-15, 2022.
- [9] S. Sadiq, M. Umer, S. Ullah, S. Mirjalili, V. Rupapara e M. Nappi, "Discrepancy detection between actual user reviews and numeric ratings of Google App store using deep learning," *Expert Systems With Applications*, vol. 181, pp. 1-8, 2021.
- [10] D. S. Bimaputra e E. Sutoyo, "Aspect-Based Sentiment Analysis of Hotels in Bali on Tripadvisor Using BERT Algorithm," *International Journal of Advances in Data and Information Systems*, vol. 4, n° 1, pp. 29-40, 2023.
- [11] Y. Gao, J. Liu, P. Li e D. Zhou, "CE-HEAT: An Aspect-Level Sentiment Classification Approach With Collaborative Extraction Hierarchical Attention Network," *IEEE Access*, pp. 168548-168556, 2019.



- [12] A. Rozaq, Y. Yunitasari, K. Sussolaikah e E. R. N. Sari, "Sentiment Analysis of Kampus Mengajar 2 Toward the Implementation of Merdeka Belajar Kampus Merdeka Using Naïve Bayes and Euclidean Distance Methods," *International Journal of Advances in Data and Information Systems*, vol. 3, n° 1, pp. 30-37, 2022.
- [13] M. J. Islam, R. Datta e A. Iqbal, "Actual rating calculation of the zoom cloud meetings app using user reviews on google play store with sentiment annotation of BERT and hybridization of RNN and LSTM," *Expert Systems With Applications*, vol. 223, pp. 1-10, 2023.
- [14] M. A. Nurrohmat e A. SN, "Sentiment Analysis of Novel Review Using Long Short-Term Memory Method," *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, vol. 13, n° 3, pp. 209-218, 2019.
- [15] U. B. Mahadevaswamy e S. P., "Sentiment Analysis using Bidirectional LSTM Network," em *International Conference on Machine Learning and Data Engineering*, 2023.
- [16] A. C. M. V. Srinivas, Ch.Satyanarayana, Ch.Divakar e K. P. Sirisha, "Sentiment Analysis using Neural Network and LSTM," em *IOP Conf. Series: Materials Science and Engineering*, 2020.
- [17] Y. Huang, Q. Liu, H. Peng, J. Wang, Q. Yang e D. Orellana-Martín, "Sentiment classification using bidirectional LSTM-SNP model and attention mechanism," *Expert Systems With Applications*, vol. 21, pp. 1-7, 2023.
- [18] D. G. S. N. Murthy, S. R. Allu e B. Andhavarapu, "Text based Sentiment Analysis using LSTM," *International Journal of Engineering Research & Technology (IJERT)*, vol. 9, n° 5, pp. 299-303, 2020.
- [19] K. A. Manurung e K. M. Lhaksmana, "Sentiment Analysis of Tourist Attraction Review from TripAdvisor Using CNN and LSTM," *Intl. Journal on ICT*, vol. 9, n° 1, pp. 73-85, 2023.
- [20] R. Eliviani e Y. Bandung, "WSN-IoT Forecast: Wireless Sensor Network Throughput Prediction Framework in Multimedia Internet of Things," *J. ICT Res. Appl.*, vol. 17, n° 3, pp. 336-355, 2023.
- [21] R. Mitchell, *Web Scraping with Python: Collecting More Data From The Modern Web*, Sebastopol: O'Reilly Media, Inc., 2018.
- [22] W. A. Wahyuni, S. Saepudin e F. Sembiring, "Sentiment Analysis of Online Investment Applications on Google Play Store using Random Forest Algorithm Method," *Jurnal Mantik*, vol. 4, pp. 2203-2209, 2022.
- [23] A. Tawakuli e T. Engel, "Towards Normalizing The Design Phase of Data Preprocessing Pipelines For IoT Data," em *IEEE International Conference on Big Data (Big Data)*, 2022.
- [24] J. Hartmann, M. Heitmann, C. Siebert e C. Schamp, "More than a Feeling: Accuracy and Application of Sentiment Analysis," *International Journal of Research in Marketing*, vol. 40, pp. 75-87, 2022.
- [25] H. Dalianis, *Clinical Text Mining: Secondary Use of Electronic Patient Records*, Cham, Switzerland: Springer International Publishing AG part of Springer Nature, 2018.