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Analysis of Zoom App User Reviews on Google Play Store Using Recurrent Neural Networks and Gated Recurrent Unit Algorithms

Muta'alimah[1*], Elsa Setiawati [2], Josephine Kwok[3], Hauriya Hasysya [4], Muhammad Atthaariq Aziiz[5]

[1,2]Department of Information Systems, Faculty of Science and Technology,
Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia
[3]Departement of Information Technology,
Singapore Institute of Management, Singapore
[4] Department of Human Resource Development, Faculty of Social Science and Humanities,
University Technology Malaysia, Malaysia
[5]Department of Aqidah Philosophy, Faculty of Ushuluddin,
Al-Azhar Ash-Sharif University, Cairo, Egypt

E-Mail: [1]12150323778@students.uin-suska.ac.id, [2]12150325178@students.uin-suska.ac.id,
[3]jkwok002@mymail.sim.edu.sg, [4]hauriya@graduate.utm.my, [5]thaariqaziiz@gmail.com

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Corresponding Author: Muta'alimah

Abstract

The World Health Organization (WHO) declared COVID-19 a global pandemic on March 11, 2020. Technology is crucial to stop the spread of the virus. Video conferencing applications such as Zoom Cloud Meetings are essential for collaboration and communication as the government issues policies to conduct various activities from home. Zoom was released in January 2013 to become a trendy video conferencing platform until now. However, post-pandemic, the Zoom App faces challenges maintaining user satisfaction due to the reduced need for virtual meetings. This research aims to analyze user reviews of the Zoom app on the Google Play Store using the RNN and Analysis of Zoom App User Reviews on Google Play Store Using Recurrent Neural Networks (RNN) and Gated Recurrent Unit Algorithms (GRU) algorithms, determine which user reviews are positive, negative, and neutral, identify common problems with Zoom for improvement recommendations, and compare the accuracy between the RNN and GRU algorithms. The results showed that out of 5000 reviews, 3728 sentiments were Positive, 1041 sentiments were Negative, and 231 sentiments were Neutral. The RNN algorithm achieved 86% accuracy, 86% precision, 100% recall, and 92% f1-score, while GRU achieved 83% accuracy, 87% precision, 92% recall, and 89% f1-score. Thus, RNN is superior in sentiment classification and most users are satisfied with the app, but negative reviews indicate areas that require improvement. This research provides valuable insights for developers to improve Zoom app features based on user feedback.

Keyword : Deep Learning, Gated Recurrent Unit, Recurrent Neural Networks, Zoom Cloud Meetings

1. INTRODUCTION

On March 11, 2020, the World Health Organization (WHO) officially declared Covid-19 as a global pandemic [1], making technology play an important role in stopping the spread of the Covid-19 virus [2]. Technology is utilized in almost all sectors because, in this condition, the government issued a policy so that all activities are carried out from home [3]. Video conferencing applications have become an important tool in supporting communication and collaboration, both in professional and personal contexts without having to meet in person [4]. The most popular application used since the pandemic until now is the Zoom Cloud Meeting application [5], [6], [7].

Zoom Cloud Meeting App, founded by Eric Yuan in 2011 and launched in January 2013, has become a trendy video conferencing platform, especially as a learning and communication tool during the COVID-19 pandemic [4]. With its ability to enable virtual meetings without physical presence, Zoom has become a top choice for millions of users worldwide[8]. During the first half of 2023, the Zoom mobile app has been downloaded more than 81.48 million times, showing its growing popularity. By 2024, the number of Zoom's daily active users will have reached 300 million, while its market share in global video conferencing software will reach 57.24% worldwide [9], [10] and be rated 4.3 in the Google Play Store [11]. However, post-pandemic, Zoom faces a major challenge in maintaining user satisfaction amidst the reduced need for virtual meetings due to the return of face-to-face activitie [12].

The main problem in this research is how Zoom can maintain user satisfaction amidst the reduced need for virtual meetings and various technical complaints. Zoom app user reviews can guide the software development process and help produce better software versions in the future that need to be further analyzed [13]. This is reflected in user reviews on the Google Play Store which complain of various issues such as connection stability, unclear audio quality, video freezes, and lack of options for portrait or landscape view settings [11]. These issues reflect the changing expectations and needs of users towards video conferencing apps in the post-pandemic era. It is important to analyze the sentiment of user reviews identify key issues and provide relevant improvement recommendations. As such, this research aims to help Zoom understand how their app can continue to meet user needs and maintain its position as a market leader in the video conferencing software industry.

This research is crucial as diverse user reviews can provide deep insights into the problems users face and desired features. Sentiment analysis of user reviews helps identify positive, negative, neutral sentiments and patterns that emerge from them. Moreover, a deep understanding of user reviews can help in maintaining user satisfaction in the future, even when the need for virtual meetings decreases. Many methods have been proposed to automatically classify user reviews, including frequently used deep learning models such as Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Gated Recurrent Unit (GRU) [14]. Unlike the previous studies, this research specifically compares the performance of RNN and GRU in classifying the sentiment of Zoom user reviews. RNN and GRU were chosen because they are capable of processing sequential data and capturing temporal dependencies in text, which is important for sentiment analysis and addressing the problem with a simpler and more efficient gating mechanism.

Some previous research on deep learning for sentiment analysis in the context of user reviews related to case studies, namely, Islam et al (2023) in this study used the RNN and LSTM algorithms where the results showed reviews had a lot of positive sentiment with RNN accuracy of 0.53% and LSTM accuracy of 0.47% [4]. The same research by Raza et al (2021) shows that the GRU algorithm produces the highest accuracy value per epoch of 0.97%, RNN accuracy of 0.96%, and LSTM accuracy of 0.95% in processing cloud user review data [15]. In Shakib's research (2023) using static permit and APIcall features, the GeneticAI classifier also shows the accuracy value of the GRU algorithm to be the highest at 99.77% compared to RNN accuracy of 99.36%, LSTM accuracy of 99.27%, and CNN accuracy of 95.93% [16]. Refianti et al s research (2023) processed Zoom Cloud Meetings user review data on the Google Play Store using the CNN deep learning model with 91.5% accuracy and classified as many as 116 positive reviews and 67 negative reviews [12]. Wahyudi and Sibaroni's research (2022) in this study used RNN and the addition of Bidirectional Encoder Representations (BERT) word embedding in Tiktok user reviews on the Google Play Store with an accuracy value of 0.95% with fairly good performance [17].

GRU and RNN are important in this research because they are designed to handle sequential data, such as text user reviews. In sentiment analysis, these algorithms are able to understand the relationship between words in context, which affects the accuracy of sentiment classification [18]. GRU, with a simpler architecture compared to LSTM, is more computationally efficient while still effectively handling long-term dependencies [19], while RNN excels at detecting sequential data patterns despite limitations such as vanishing gradient [20].

The selection of these two algorithms is not only based on the accuracy of previous research, but also the suitability to the context of the problem. Previous research shows GRU and RNN perform well in sentiment classification, making them relevant for use on the post-pandemic Zoom review dataset. Therefore, the researcher raised the title "Analysis of Zoom App User Reviews on the Google Play Store using the RNN and GRU algorithms" which aims to determine whether user reviews are positive, negative, and neutral [4], identify common problems with Zoom for improvement recommendations, and compare the accuracy of the two algorithms[3], [14]. The urgency and novelty of this research lies in the specific focus on post-pandemic Zoom, offering specific insights for developers, as well as enriching the literature with a direct comparison between RNN and GRU in the context of sentiment analysis.

2. MATERIAL AND METHOD

2.1. Analysis Sentiment

Sentiment of analysis is the process of identifying and categorizing users' emotions or opinions about services, such as movies, products, events, or other attributes, whether they are positive, negative, or neutral [21]. Sentiment analysis techniques have been developed to analyze reviews and understand the impression conveyed by the reviews [22]. Sentiment Analysis identifies the sentiment expressed in a text and then analyzes it [23]. There are three main classifications in Sentiment Analysis: document level, sentence level, and aspect level. Sentiment analysis, also known as opinion mining, provides information about what people like or dislike. With this information, companies can better understand their customers' views on the features of their products.

2.2 Data Scraper

Data scraper, often called web scraper, is a data mining technology used to extract unstructured data from various online sources, then convert it into a structured form to be stored and analyzed in a database [24]. The benefit of a good web scraper is its ability to automatically collect data from targeted sources and turn it into a collection of useful information [25]. Data scrapers can be used to extract information from websites such as text, images, and metadata, which can then be analyzed or stored for various purposes, such as market research, price monitoring, and data collection for deep learning.

2.3 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNN) is a type of neural network that has connections between neurons that form directed cycles, creating a feedback loop within the network that automatically keeps information from the past stored can be seen as a visualization of a slice of an RNN A in Figure 1. The main function of RNN is sequential information processing based on internal memory captured by directed cycles [26]. RNNs use information from past inputs and current inputs, which is very beneficial when predicting time series data [27]. For ease of understanding here is a simple overview and how RNN predicts the character of the looping RNN [28].

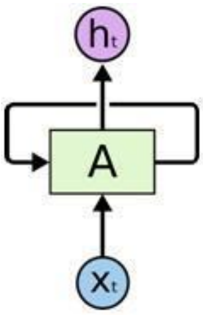

Figure 1. Recurrent Neural Network loop

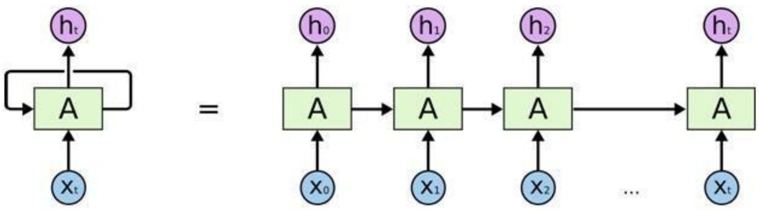

Figure 2. Past Information Transmission on Looping RNN

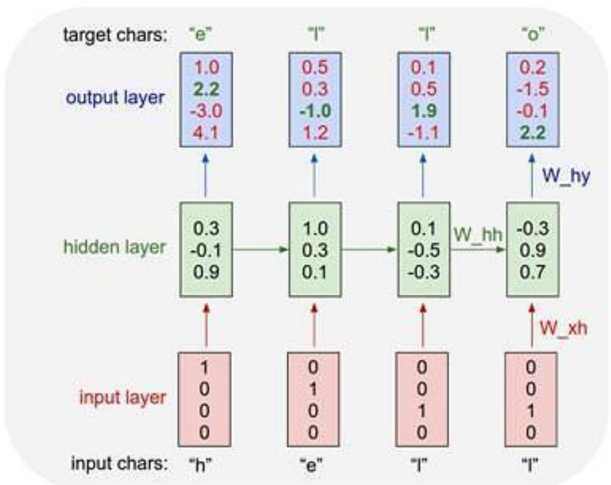

Figure 3. RNN Process Performs Prediction

Based on Figures 2 and 3, the RNN processes the input data sequentially one by one from the letters "h" to "l". The hidden layer will send the data to the next hidden layer at the next time. This process takes place sequentially. 'al' refers to the input layer, 'hdl' refers to the hidden layer, and 'cl' is used for the output layer. X, Y, and Z are the network parameters that contribute to the output. At the time 't', the current state consists of the combined input 'al(t)' and the previous hidden state 'hdlt-1". This results in the expression of the current state of the network by using the following formula 1-3 [15].

$$\mathrm{hdl_t} = (\mathrm{hdl_{t-1}}, \mathrm{al_t}) \tag{1}$$

$$\mathrm{hdl_t} = \tanh(\mathrm{W_{hdl}} \times \mathrm{hdl_{t-1}} + \mathrm{w_{al}} \times \mathrm{al_t}) \tag{2}$$

$$\mathrm{cl_t} = \mathrm{W_{cl}} \times \mathrm{hdl_t} \tag{3}$$

2.4 Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is one type of architecture in recurrent neural networks (RNNs), the most popular with specialized artificial neural networks driven by special gates based on optimized LSTM [29]. Like Long Short-Term Memory (LSTM), GRU also overcomes the vanishing gradient problem that occurs in RNNs. GRU has a similar architecture to LSTM as can be seen in Figure 4, but it is simpler because GRU has no cell state (Ct) and uses fewer gates[30]. GRU has two types of gates: the first gate is update, which governs the extent to which previous information is retained in the current state, and the second gate is reset, which determines whether previous information will be merged with the current state[31]. Formulas 4-7 that can be used[32], [33].

$$\mathrm{v_t} = \sigma(\mathrm{W_v}.\left[\mathrm{Y_{t-1}}, \mathrm{Z_t}\right] + \mathrm{b_v} \tag{4}$$

$$\mathrm{r_t} = \sigma(\mathrm{W_r}.[\mathrm{Y_{t-1}}, \mathrm{Z_t}] + \mathrm{b_r}) \tag{5}$$

$$\mathrm{h_t} = \tanh(\mathrm{W_h}.[\mathrm{r_t}.\mathrm{Y_{t-1}}, \mathrm{Z_t}] + \mathrm{b_h}) \tag{6}$$

$$\mathrm{Y_t} = (1 - \mathrm{v_t}).\mathrm{Y_{t-1}} + \mathrm{v_t}.\mathrm{h_t} \tag{7}$$

In the GRU model, there are several main components that work synergistically to process sequential data. The first component is the gate update ($\mathrm{v_t}$), which governs the extent to which information from the previous state ($\mathrm{Y_{t-1}}$) will be retained into the current state. The value of ($\mathrm{v_t}$), is calculated by applying a sigmoid gate network layer (σ) to the linear combination of the current input and the previous state, which is represented by the weight matrix ($\mathrm{W_v}, \mathrm{W_r}, \mathrm{W_h}$) . Furthermore, the reset gate ($\mathrm{r_t}$) determines how much of the previous state's contribution will be used to calculate the candidate hidden state ($\mathrm{h_t}$). Reset gate ($\mathrm{r_t}$) is also calculated with a sigmoid function applied to the weight matrix ($\mathrm{W_v}, \mathrm{W_r}, \mathrm{W_h}$) . Then, ($\mathrm{h_t}$) is obtained using the tanh activation function, which combines the reset gate ($\mathrm{r_t}$), the previous state ($\mathrm{Y_{t-1}}$), and the weight matrix ($\mathrm{W_v}, \mathrm{W_r}, \mathrm{W_h}$). Akhirnya, final hidden state ($\mathrm{Y_t}$) is calculated as an interpolation between the candidate hidden state ($\mathrm{h_t}$) and the previous state ($\mathrm{Y_{t-1}}$), where this interpolation is controlled by the update gate ($\mathrm{v_t}$). The role of these components ensures GRU can efficiently handle long-term dependencies in sequential data.

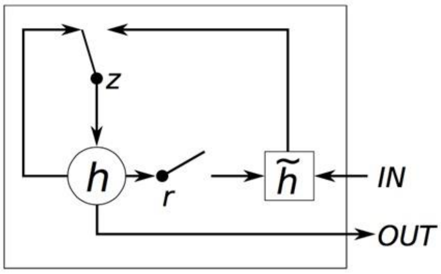

Figure 4. Arsitektur GRU

In Figure 4, r represents reset gates and z represents update gates. Meanwhile, h and ĥ represent activation and candidate activation. Activation and candidate activation are activation functions[34].

2.5 Method

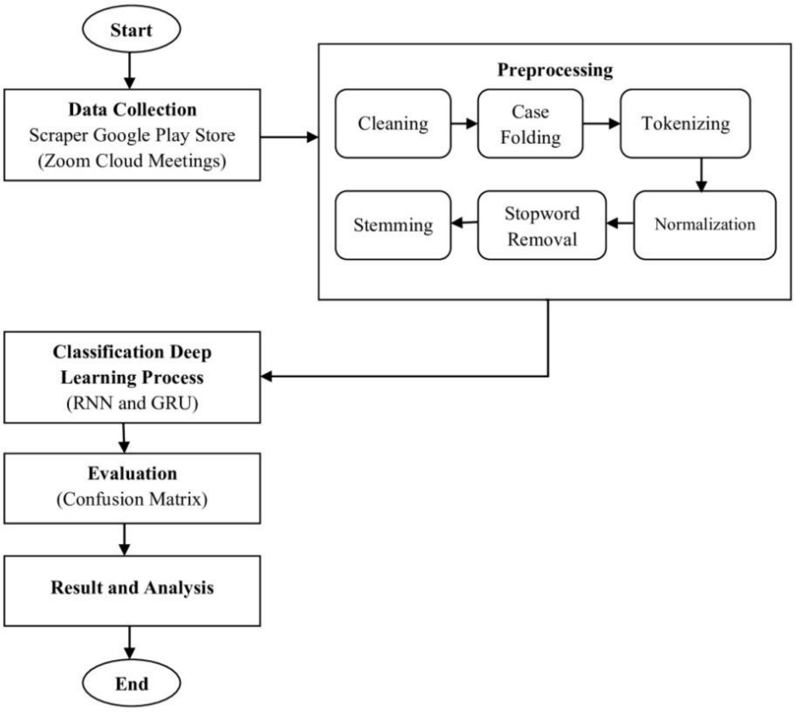

Figure 5. Research Methodology

The research methodology in this study begins with data collection [35], where user reviews of the Zoom application on the Google Play Store are scraped to gather the latest data. This process ensures a comprehensive and up-to-date dataset for analysis. Following data collection, the preprocessing stage is carried out to prepare the raw data into a structured and usable format. Preprocessing involves six essential steps [12]: cleaning (removing irrelevant attributes such as punctuation, empty characters, and emojis), case folding (converting all text to lowercase), tokenizing (breaking sentences into individual words), normalization (correcting word errors and ensuring consistency in word meanings), stopword removal (eliminating insignificant words), and stemming (reducing words to their root forms). These steps collectively enhance data quality and improve model performance in subsequent stages.

Once preprocessing is complete, the classification process employs deep learning models, specifically RNN and GRU, to classify sentiment in the review data. The performance of these models is evaluated using a confusion matrix, which provides key metrics such as accuracy, precision, recall, and f1-score [15]. The final stage involves presenting the results and analysis, where the algorithm with the highest accuracy is identified, and the sentiment analysis of user reviews is thoroughly discussed.

3. RESULTS AND DISCUSSION

This section presents the results of an in-depth analysis of Zoom Cloud Meetings App user reviews collected from the Google Play Store. This analysis systematically outlines the steps in finding sentiment results and compares the implementation of the RNN and GRU deep learning algorithms using Google Colab.

3.1. Data Collection

The initial stage in this research is data collection. The data used as the object of research are user reviews of the Zoom Cloud Meeting application on the Google Play Store. A similar dataset was previously used in research by [3], [4], [12], which also analyzed Zoom user reviews on the Google Play Store. The research shows good results in sentiment classification, thus supporting the use of this dataset for further research.

This research uses Google Collab and scrapping. The scrapping results in 5000 records, and is public data retrieved based on the Sort.NEWEST parameter. Only 4 attributes are used, namely username, content, score, and date from 11 available attributes. This is because the other 7 attributes are not the focus of research related to user reviews of the Zoom Cloud Meeting application on the Google Play Store, which can be seen in Table 1.

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Table 1. Data Collection

	Username	Content	Score	At
0	Collin Castinger	Oke..banget	5	2024-05-29 07:09:51
1	Sukarno bimma	Mamtap	5	2024-05-29 06:36:56
2	M Darwin	Woow Muantab keren banget..!!!♡♡♡♡♡♡👍👍👍👍...	5	2024-05-29 06:12:03
3	Apritama Putra Gafur	👍	1	2024-05-29 04:40:35
4	Yudi Setiadi	good aplication	4	2024-05-29 04:04:37
…	…	…	…	…
4999	Ratri Dwi	Aplikasi sangat bagus😎	5	2023-10-02 13:18:46

3.2. Preprocessing

In this stage, the collected review data is prepared for the next step. The process involves cleaning, splitting into tokens, removal of unimportant words, and word trimming. This preprocessing process was carried out using Google Collaboratory using the Python programming language.

In the cleaning stage, the data is cleaned by removing attributes that are not relevant for classification, such as emojis, special characters, and converting text to lowercase as can be seen in table 2. The raw data obtained still has attributes such as username, date, and other attributes that are not relevant for sentiment analysis. Therefore, a data cleaning stage is required to remove these attributes so that the data can be processed further in sentiment analysis. Next, case folding is a process where all letters in the text are converted into lowercase letters. The goal is to maintain the consistency of letter writing so that all letters become lowercase. In this way, the processed text will become more uniform so as to facilitate interpretation and further analysis.

In the tokenization stage, text data is broken down into separate units called tokens. These tokens can consist of words or symbols that have meaning or relevance in a particular context as seen in table 3. then in the stopwords removal stage, the process of removing common words that tend not to contribute significantly to the analysis. In table 4. is the stopwords removal stage is the process of removing common words that tend not to contribute significantly to the analysis, such as conjunctions or pronouns, as well as words that appear frequently but do not provide important information. In the stemming stage, text processing is carried out with the aim of reducing words to their basic form or root words, which are referred to as stems. This stemming process involves the removal of prefixes and suffixes of words so that only the core part of the word remains can be seen in Table 5.

Table 2. Text Cleaning

No	Username	Score	At	Text_Tokenize
0	Collin Castinger	5	2024-05-29 07:09:51	oke banget
1	Sukarno bimma	5	2024-05-29 06:36:56	mamtap
2	M Darwin	5	2024-05-2906:12:03	woow, muantab, keren, banget
3	Apritama Putra Gafur	1	2024-05-29 04:40:35	
4	Yudi Setiadi	4	2024-05-29 04:04:37	good, application

Table 3. Text Tokenize

No	Username	Score	At	Text_Tokenize
0	Collin Castinger	5	2024-05-29 07:09:51	[oke, banget]
1	Sukarno bimma	5	2024-05-29 06:36:56	[mamtap]
2	M Darwin	5	2024-05-2906:12:03	[woow, muantab, keren, banget]
3	Apritama Putra Gafur	1	2024-05-29 04:40:35	[]
4	Yudi Setiadi	4	2024-05-29 04:04:37	[good, application]

Table 4. Remove Stopword

No	Username	Score	At	Remove_Stopword
0	Collin Castinger	5	2024-05-29 07:09:51	[oke, banget]
1	Sukarno bimma	5	2024-05-29 06:36:56	[mamtap]
2	M Darwin	5	2024-05-2906:12:03	[woow, muantab, keren, banget]
3	Apritama Putra Gafur	1	2024-05-29 04:40:35	[]
4	Yudi Setiadi	4	2024-05-29 04:04:37	[good, application]

Table 5. Stemming Result

No	Username	Score	At	Stemming
0	Collin Castinger	5	2024-05-29 07:09:51	[oke, banget]
1	Sukarno bimma	5	2024-05-29 06:36:56	[mamtap]
2	M Darwin	5	2024-05-2906:12:03	[woow, muantab, keren, banget]
3	Apritama Putra Gafur	1	2024-05-29 04:40:35	[]
4	Yudi Setiadi	4	2024-05-29 04:04:37	[good, application]

3.3 Sentiment Identification Results

In the next stage, create data labeling to determine the sentiment obtained from the preprocessing results. Review data labeling uses two types, namely Positive and Negative. A rating value <3 is considered negative, a rating value =3 is considered neutral, while a rating value >3 is considered positive. The previous data parameter is score adjusted to sentiment can be seen in Table 6.

Tabel 6. Identifikasi Sentiment

	Username	Sentiment	At	Text	Label
0	Collin Castinger	Positif	2024-05-29 07:09:51	oke banget	2
1	Sukarno bimma	Positif	2024-05-29 06:36:56	mamtap	2
2	M Darwin	Positif	2024-05-2906:12:03	woow muantab keren banget	2
3	Apritama Putra Gafur	Negatif	2024-05-29 04:40:35		0
4	Yudi Setiadi	Positif	2024-05-29 04:04:37	good aplication	2
…	…	…	…	…	…
4996	Arla Putra	Netral	2023-10-02 14:55:28	bug salin kode tulis gabung rapaturl	1
…	…	…	…	…	…
4999	Ratri Dwi	Positif	2023-10-02 13:18:46	aplikasi bagus	2

In Table 6 above, we have successfully classified the data into three sentiment groups, namely 3728 Positive sentiments, 1041 Negative sentiments, and 231 Neutral sentiments. of the total 5000 user reviews of the Zoom Cloud Meetings App on Google Play Store seen in Figure 6. This reflects that the majority of users are satisfied with various aspects of this app. However, some negative reviews indicate certain areas where the app needs improvement and enhancement.

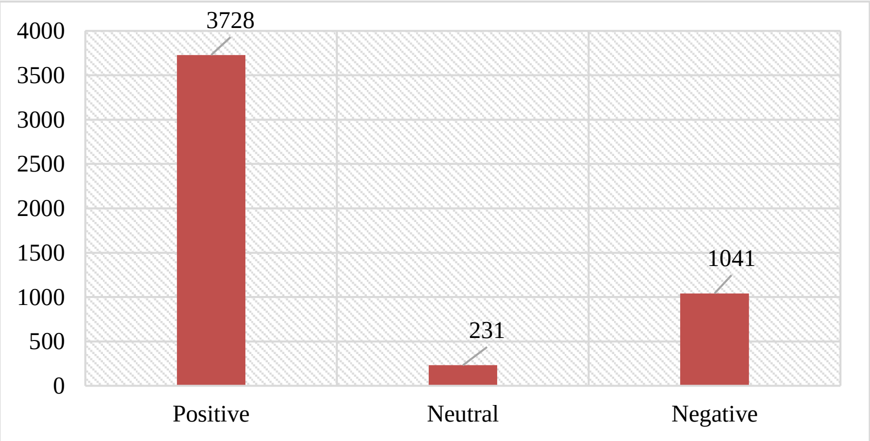

Figure 6. Sentiment Result Diagram

Then a word cloud visualization is performed with each positive, negative, and neutral sentiment to identify the words that appear most frequently in comments related to user reviews of the Zoom Cloud Meeting App on the Google Play Store. The results of the word cloud visualization are shown in Figure 7-9.

The visualization results above provide a clear picture of the dominant words in each sentiment category, helping in understanding the user's perception of the app. By separating the words by sentiment, it is possible to see key differences in user experience and feedback, which can be used to improve the quality and performance of the Zoom app.

Figure 7. Result in Wordcloud Positif

Figure 8. Result in Wordcloud Negatif

Figure 9. Result in Wordcloud Neutral

3.4 Evaluation Classification RNN and GRU Algorithm

The application of the RNN and GRU classification algorithms was carried out using Google Collab and the dataset described above. The RNN classification model used is SimpleRNN, RMSprop optimizer, and epoch size of 20 to determine the loss value and accuracy based on the confusion matrix, data used training and validation data. The results of the accuracy and loss visualization of the RNN algorithm can be seen in Figure 10.

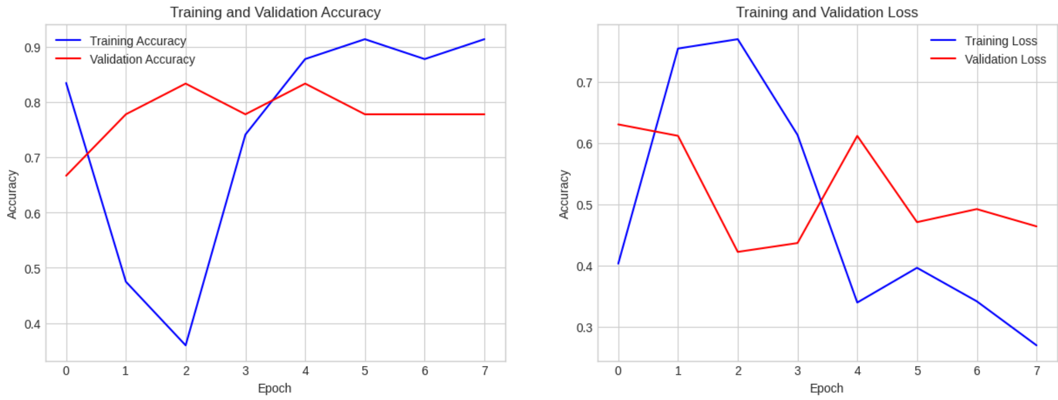

Figure 10. RNN Visualization Results

The visualization results of the RNN algorithm obtained a loss value of 38% and an accuracy of 86%. The GRU classification model uses the Adam optimizer and an epoch size of 20 to determine the loss value and accuracy based on the confusion matrix, the data used is training and validation data. The visualization results of the accuracy and loss of the GRU algorithm can be seen in Figure 11.

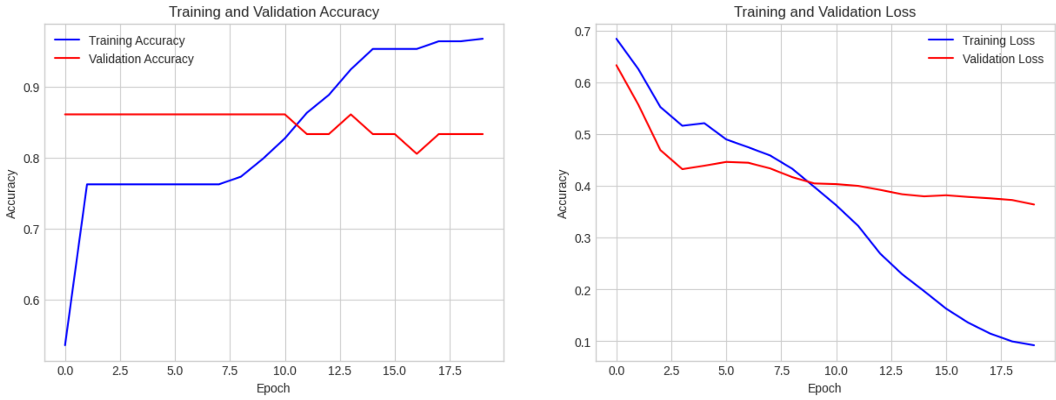

Figure 11. GRU Visualization Results

Based on the visualization results of the RNN and GRU algorithms using training and validation data, the accuracy described in the form of a confusion matrix can be seen in Table 7.

Table 7. Confusion Matrix RNN dan GRU

	Accuracy	Precision	Recall	F1-Score
RNN	0,86	0,86	1,00	0,92
GRU	0,83	0,87	0,92	0,89

Based on the results of sentiment classification with RNN and GRU modeling above, it can be seen that the best classification results on the Zoom Cloud Meeting Application User Reviews on the Google Play Store are obtained by the RNN algorithm which can be seen in the comparison diagram in Figure 12.

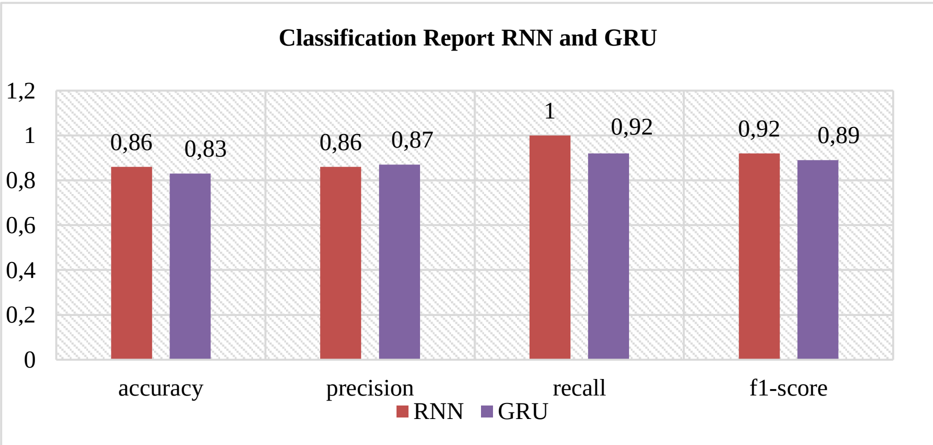

Figure 12. Comparison of Sentiment Classification Algorithm Results

The graph above explains the confusion matrix results in the RNN algorithm achieving an accuracy of 86%, a precision of 86%, a recall of 100%, and an f1-score of 92% while the GRU algorithm has an accuracy of 83%, a precision of 87%, recall 92%, and f1-score of 89%. Comparing these two algorithms, the RNN algorithm in terms of sentiment classification is superior in accuracy, recall, and f1-score.

4. CONCLUSION

In this study analyzing user reviews of the Zoom app on the Google Play Store using the RNN and GRU algorithms, the results of this study provide a better understanding of user sentiment towards the Zoom app, which is a popular video conferencing tool especially during the Covid-19 pandemic. From the classification evaluation results using the RNN and GRU algorithms, it can be concluded that the RNN algorithm performed better than GRU in terms of accuracy, recall, and F1-Score. RNN has an accuracy of

86%, while GRU has an accuracy of 83%. This shows that the RNN classification model is more effective in classifying the sentiment of user reviews. In addition, the results of the sentiment identification process show that the positive sentiment class is 3,728 reviews, the negative sentiment class is 1,041, and the neutral sentiment class is 231 reviews from a total of 5,000 Zoom Cloud Meetings App user reviews on the Google Play Store.

This research has successfully demonstrated the potential of deep learning algorithms, specifically RNN and GRU, in automatically analyzing user sentiment towards the Zoom app. The analysis results provide valuable insights for developers in an effort to improve the quality of the app based on user feedback. Nonetheless, this research has limitations in generalizing the results, as it only focuses on the Indonesian language. For future research, it is recommended to conduct a multilingual analysis to obtain a more comprehensive picture of user sentiment globally.

REFERENCES

[1] D. Cucinotta and M. Vanelli, "WHO declares COVID-19 a pandemic," *Acta Biomed.*, vol. 91, no. 1, pp. 157–160, 2020, doi: 10.23750/abm.v91i1.9397.

[2] D. Ferdiansah, O. D. Pranata, and H. Herayati, "The EFL Students ' Perception on Zoom Meeting as a Teaching Platform : A Survey Research," *IDEAS J. English Lang. Teach. Learn. Linguist. Lit.*, vol. 12, no. 1, pp. 222–235, 2024, doi: 10.24256/ideas.v12i1.4015.

[3] Janu Akrama Wardhana and Yuliant Sibaroni, "Aspect Level Sentiment Analysis on Zoom Cloud Meetings App Review Using LDA," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 5, no. 4, pp. 631–638, 2021, doi: 10.29207/resti.v5i4.3143.

[4] M. J. Islam, R. Datta, and 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 Syst. Appl.*, vol. 223, no. June 2022, p. 119919, 2023, doi: 10.1016/j.eswa.2023.119919.

[5] "Analitik Zoom," explore.zoom. Accessed: Jun. 02, 2024. [Online]. Available: https://explore.zoom.us/id/zoom-analytics/

[6] M. A. Rizaty, "Pendapatan Zoom Naik 12,3% pada Kuartal I 2022." Accessed: Jun. 02, 2024. [Online]. Available: https://databoks.katadata.co.id/datapublish/2022/06/21/pendapatan-zoom-naik-123-pada-kuartal-i-2022

[7] DivaAngelia, "Platform Online Meeting Terpopuler Selama Pandemi Covid-19." Accessed: Jun. 02, 2024. [Online]. Available: https://goodstats.id/article/platform-online-meeting-paling-populer-selama-pandemi-covid-19-oDElB

[8] A. Haling, S. N. Ilmi, and A. D. Astuty, "Teaching Practice in a Shifting to Post-Covid 19 Era: A Study from Indonesian Higher Institution," *Qwerty. Open Interdiscip. J. Technol. Cult. Educ.*, vol. 0, no. 0, 2024, doi: 10.30557/qw000074.

[9] R. Shewale, "15 Statistik Pengguna & Pendapatan Zoom (2024)," Ddemandsage. Accessed: Jun. 05, 2024. [Online]. Available: https://www.demandsage.com/zoom-statistics/

[10] M. Iqbal, "Statistik Pendapatan dan Penggunaan Zoom (2024)," Business of Apps. Accessed: Jun. 05, 2024. [Online]. Available: https://www.businessofapps.com/data/zoom-statistics/

[11] "Ulasan Aplikasi Zoom Meeting," Google Play. Accessed: Jun. 05, 2024. [Online]. Available: https://play.google.com/store/apps/details?id=us.zoom.videomeetings&hl=en-ID

[12] R. Refianti and N. Anggraeni, "Sentiment Analysis Using Convolutional Neural Network Method to Classify Reviews on Zoom Cloud Meetings Application Based on Reviews on Google Playstore," *Int. J. Eng. Sci. Inf. Technol.*, vol. 3, no. 3, pp. 7–16, 2023, doi: 10.52088/ijesty.v3i3.463.

[13] D. Pratmanto, R. Rousyati, F. F. Wati, A. E. Widodo, S. Suleman, and R. Wijianto, "App Review Sentiment Analysis Shopee Application in Google Play Store Using Naive Bayes Algorithm," *J. Phys. Conf. Ser.*, vol. 1641, no. 1, 2020, doi: 10.1088/1742-6596/1641/1/012043.

[14] M. Razavi, H. Rastegari, A. Nabiollahi-najafabadi, and T. Javdani Gandomani, "User Reviews Classification in Play Store Applications Using Deep Learning : An Empirical Study," *Diqiu Kexue*, vol. 48, no. 6, pp. 43–57, 2023, doi: 10.3799/dqkx.2023.8163.

[15] M. R. Raza, W. Hussain, and J. M. Merigo, "Cloud Sentiment Accuracy Comparison using RNN, LSTM and GRU," *Proc. - 2021 Innov. Intell. Syst. Appl. Conf. ASYU 2021*, no. March, 2021, doi: 10.1109/ASYU52992.2021.9599044.

[16] M. H. Shakib, "Android Malware Detection Approach's Based on Genetic AI, CNN, RNN, LSTM, GRU, and Active Learning.," 2023.

[17] D. Wahyudi and Y. Sibaroni, "Deep Learning for Multi-Aspect Sentiment Analysis of TikTok App using the RNN-LSTM Method," *Build. Informatics, Technol. Sci.*, vol. 4, no. 1, pp. 169–177, 2022, doi: 10.47065/bits.v4i1.1665.

[18] K. E. ArunKumar, D. V. Kalaga, C. M. S. Kumar, M. Kawaji, and T. M. Brenza, "Forecasting of COVID-19 using deep layer Recurrent Neural Networks (RNNs) with Gated Recurrent Units (GRUs)

and Long Short-Term Memory (LSTM) cells," *Chaos, Solitons and Fractals*, vol. 146, p. 110861, 2021, doi: 10.1016/j.chaos.2021.110861.
[19] Q. Liu, M. Yu, and M. Bai, "A study on a recommendation algorithm based on spectral clustering and GRU," *iScience*, vol. 27, no. 2, p. 108660, 2024, doi: 10.1016/j.isci.2023.108660.
[20] F. Shan, X. He, D. J. Armaghani, and D. Sheng, "Effects of data smoothing and recurrent neural network (RNN) algorithms for real-time forecasting of tunnel boring machine (TBM) performance," *J. Rock Mech. Geotech. Eng.*, vol. 16, no. 5, pp. 1538–1551, 2024, doi: 10.1016/j.jrmge.2023.06.015.
[21] P. Mehta and S. Pandya, "A review on sentiment analysis methodologies, practices and applications," *Int. J. Sci. Technol. Res.*, vol. 9, no. 2, pp. 601–609, 2020.
[22] R. Obiedat, D. Al-Darras, E. Alzaghoul, and O. Harfoushi, "Arabic Aspect-Based Sentiment Analysis: A Systematic Literature Review," *IEEE Access*, vol. 9, pp. 152628–152645, 2021, doi: 10.1109/ACCESS.2021.3127140.
[23] S. Suryani, M. F. Fayyad, D. T. Savra, V. Kurniawan, and B. H. Estanto, "Sentiment Analysis of Towards Electric Cars using Naive Bayes Classifier and Support Vector Machine Algorithm," *Public Res. J. Eng. Data Technol. Comput. Sci.*, vol. 1, no. 1, pp. 1–9, 2023, doi: 10.57152/predatecs.v1i1.814.
[24] N. Shah, J. Li, and T. K. Mackey, "An unsupervised machine learning approach for the detection and characterization of illicit drug-dealing comments and interactions on Instagram," *Subst. Abus.*, vol. 43, no. 1, pp. 273–277, 2022, doi: 10.1080/08897077.2021.1941508.
[25] H. Lan *et al.*, "COVID-Scraper: An Open-Source Toolset for Automatically Scraping and Processing Global Multi-Scale Spatiotemporal COVID-19 Records," *IEEE Access*, vol. 9, pp. 84783–84798, 2021, doi: 10.1109/ACCESS.2021.3085682.
[26] A. Chamekh, M. Mahfoudh, and G. Forestier, "Sentiment Analysis Based on Deep Learning in E-Commerce," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 13369 LNAI, pp. 498–507, 2022, doi: 10.1007/978-3-031-10986-7_40.
[27] K. Park, Y. Choi, W. J. Choi, H. Y. Ryu, and H. Kim, "LSTM-Based Battery Remaining Useful Life Prediction with Multi-Channel Charging Profiles," *IEEE Access*, vol. 8, pp. 20786–20798, 2020, doi: 10.1109/ACCESS.2020.2968939.
[28] N. Putu and N. Kusuma, "Prediksi Harga Saham Blue Chip Pada Indeks Idx30 Menggunakan Algoritma Recurrent Neural Network (RNN)," vol. 23, no. 1, pp. 90–97, 2024.
[29] S. Mahjoub, L. Chrifi-Alaoui, B. Marhic, and L. Delahoche, "Predicting Energy Consumption Using LSTM, Multi-Layer GRU and Drop-GRU Neural Networks," *Sensors*, vol. 22, no. 11, pp. 1–20, 2022, doi: 10.3390/s22114062.
[30] A. S. Girsang and Stanley, "Hybrid LSTM and GRU for Cryptocurrency Price Forecasting Based on Social Network Sentiment Analysis Using FinBERT," *IEEE Access*, vol. 11, no. September, pp. 120530–120540, 2023, doi: 10.1109/ACCESS.2023.3324535.
[31] L. Wu, C. Kong, X. Hao, and W. Chen, "A Short-Term Load Forecasting Method Based on GRU-CNN Hybrid Neural Network Model," *Math. Probl. Eng.*, vol. 2020, 2020, doi: 10.1155/2020/1428104.
[32] C. Zeng, C. Ma, K. Wang, and Z. Cui, "Parking Occupancy Prediction Method Based on Multi Factors and Stacked GRU-LSTM," *IEEE Access*, vol. 10, pp. 47361–47370, 2022, doi: 10.1109/ACCESS.2022.3171330.
[33] K. Karunia, A. E. Putri, M. D. Fachriani, and M. H. Rois, "Evaluation of the Effectiveness of Neural Network Models for Analyzing Customer Review Sentiments on Marketplace," *Public Res. J. Eng. Data Technol. Comput. Sci.*, vol. 2, no. 1, pp. 52–59, 2024, doi: 10.57152/predatecs.v2i1.1100.
[34] A. Rolangon, A. Weku, and G. A. Sandag, "Perbandingan Algoritma LSTM Untuk Analisis Sentimen Pengguna Twitter Terhadap Layanan Rumah Sakit Saat Pandemi Covid-19," *TeIKa*, vol. 13, no. 01, pp. 31–40, 2023, doi: 10.36342/teika.v13i01.3063.
[35] M. Muta'alimah, C. K. Zarry, A. Kurniawan, H. Hasysya, M. F. Firas, and N. Nadhirah, "Classifications of Offline Shopping Trends and Patterns with Machine Learning Algorithms," *Public Res. J. Eng. Data Technol. Comput. Sci.*, vol. 2, no. 1, pp. 18–25, 2024, doi: 10.57152/predatecs.v2i1.1099.