Jurnal Ilmiah
Teknologi Sistem
Informasi

Vol. 6 (2025) No. 3

https://jurnal-itsi.org/index.php/jitsi; E-ISSN: 2722-4600; ISSN: 2722-4619
DOI: 10.62527/jitsi.6.3.460

Sentiment Analysis of Pinterest Application User Reviews Using ANN, CNN, and RNN Methods

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ABSTRACTS

The changes occurring in the pinterest application have sparked numerous opinions expressed on google playstore, both positive and negative. The purpose of this study is to analyze the sentiment of Indonesian public towards the Pinterest application through user reviews on the platform. The research method employed in this study is qualitative, utilizing data collection techniques through scraping user reviews and interviews. The research was conducted from October 2024 to January 2025. The data used consists of 2000 reviews collected in the years 2023 and 2024. This research uses 3 deep learning methods because they can understand large amounts of data. Others prefer machine learning as their research method because it is easier and less complicated. The RNN method is an effective method for performing sentiment analysis with large amounts of data. This is supported by research results indicating that the RNN (Recurrent Neural Networks) method achieved the highest accuracy in sentiment analysis, reaching 65.17%, followed by two other deep learning methods, namely CNN (Convolutional Neural Networks) and ANN (Artificial Neural Networks). The RNN method is effective because it is supported by high precision and recall values. The author suggests that future research should explore other methods and expand data from different platforms to gain a broader perspective.

Manuscript received Jun 19, 2025; revised Jul 24, 2025. accepted Jul 26, 2025 Date of publication Sep 30, 2025. International Journal, JITSI : Jurnal Ilmiah Teknologi Sistem Informasi licensed under a Creative Commons Attribution-Share Alike 4.0 International License

Keywords / Kata Kunci — ***Sentiment; Pinterest; Google Playstore Reviews; Deep Learning Method; Recurrent Neural Network***

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1. INTRODUCTION

The development of digital technology has transformed various aspects of human life, one of which is the way society interacts and shares information. Social media has emerged as a primary means that enables communication across borders and time. One of the popular social media platforms, especially among creative professionals such as designers and photographers, is Pinterest. This application provides a variety of visual references that assist users in seeking inspiration for various projects[1]. However, like other applications, Pinterest is not free from criticism and user reviews that describe their experiences, both in terms of usability, feature quality, and technical performance.

In the context of digital applications, Google Playstore plays a crucial role with its user reviews[2]. These reviews not only reflect user satisfaction or dissatisfaction but also serve as a valuable data source for application developers to understand user needs and expectations. The sentiment contained in user reviews often reflects the overall quality of the application[3]. Positive reviews can encourage new users to try the application, while negative reviews can adversely affect the application's reputation and decrease download rates[4].

Sentiment analysis is one of the methods used to extract opinions from user reviews. This technique allows for the identification of sentiment patterns[5], both positive and negative, through automated text processing. In a world increasingly reliant on data, sentiment analysis has become an essential tool to help companies understand public opinion more deeply[6]. By using machine learning algorithms, such as Artificial Neural Networks, (Convolutional Neural Networks, and Recurrent Neural Networks, sentiment analysis can be performed with high accuracy[7]. RNN is chosen because it is a method that is compatible with large data and is capable of remembering information from previous steps.

This research focuses on the sentiment analysis of user reviews of the Pinterest application collected from Google Playstore[8]. Deep learning methods, namely ANN, CNN, and RNN, were chosen to evaluate the sentiment from the processed data. Each of these methods has its own advantages in analyzing text data. ANN can process large amounts of data with an artificial neural network structure, CNN excels in identifying patterns in structured data, while RNN is designed to process sequential data by considering previous context.

With the increasing number of reviews on platforms like Google Playstore, it is important for developers to respond appropriately to user feedback[9]. This not only helps improve the quality of the application but also strengthens user trust. This research aims to answer two main questions: what is the sentiment of the Indonesian public towards the Pinterest application as conveyed through reviews on Google Playstore[10], and which deep learning method has the best accuracy in analyzing that sentiment.

The results of this research are expected to contribute to the development of the Pinterest application[11], particularly in understanding user perceptions. Additionally, the aim of this study is to recommend effective deep learning methods for sentiment analysis. Thus, this research is not only relevant for application developers but also provides benefits for academics and practitioners interested in the fields of data analysis and machine learning

2. Research Methodology

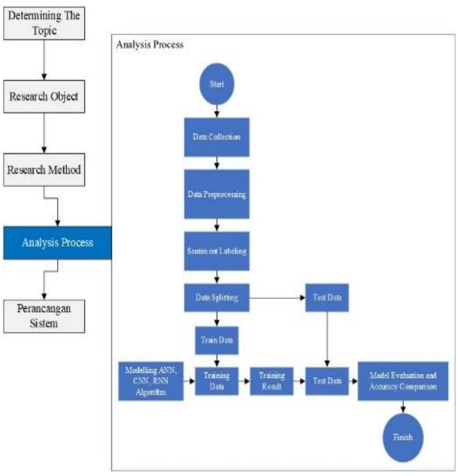


FIG 1. Research Stages

A. Determining the Topic

The first step in the research is to determine the topic to be addressed. The topic chosen for this research is sentiment analysis. This topic was selected because it can help understand public opinion quickly and effectively.

B. Research Object

The second step is the research object. The research object is something that will be studied and becomes the main target to be achieved in order to solve the problems that arise. The research object is the Pinterest application available on the Google Playstore[12]. This research is expected to help the author distinguish between positive and negative sentiments and find accurate method among the ANN, CNN, and RNN algorithms.

C. Research Method

The third step is the research method. The method used in this research is qualitative. Qualitative methods are descriptive in nature and tend to use in-depth analysis. The type of method used in this research is literature study. Literature study is a data collection technique obtained by studying and reading reference books that are relevant to the issues to be discussed, which will later assist in developing the writing concept. Sources are usually taken from reading materials such as e-books and e-journals as references[13]. Then there is data scraping, which is a data collection method by extracting data from the internet. In this research, user reviews on Google Playstore are used. From the 10 million user reviews available on Google Playstore for the Pinterest application, 20,000 user review data will be scraped and used for training and testing the data model. Lastly, there are interviews, which will make the research easier as the researcher can directly ask Pinterest application consumers questions that lead to how important public opinion about the Pinterest application is to them[14].

D. Analysis Process

The fourth step is the analysis process. The analysis process is also divided into several stages:

1. Data Collection
   The first is data collection. The data used in this research is obtained from Google Playstore reviews of the Pinterest application, which is formatted as a .csv file for management purposes.

2. Data Preprocessing
   Next is data cleaning or data preprocessing. The preprocessing stage is a data cleaning phase because the obtained data often contains irrelevant information, so it needs to be cleaned before being used for analysis. The data preprocessing process includes removing special characters, stopwords removal, tokenization, and stemming[15]. The data is cleaned of irrelevant characters such as punctuation, numbers, or special characters. Next, common words that do not provide significant meaning in the analysis, such as "and," "or," "that," are removed so that the existing data is more relevant[16]. Then, the text is broken down into individual words for further processing. Finally, words are converted to their base forms to reduce variations of words that have the same or similar meanings. The output of the data preprocessing is a clean dataset ready for sentiment labeling.
3. Sentiment Labeling
   Then there is the sentiment labeling stage. In this stage, each cleaned text is classified into positive, negative, and neutral sentiment categories.
4. Data Splitting
   The next stage is data splitting. This stage is performed to divide the dataset into two parts: train and test. The train is the largest part of the dataset used to train the model to understand patterns in the data[17]. The test is a smaller part of the dataset used to test the model's performance after training to ensure that the analysis results are not biased.
5. Method Implementation
   The next stage is method implementation. In this stage, an item from the dataset is assigned to a class label. In this research, the method implementation stage is carried out to implement the ANN, CNN, and RNN algorithms on the training data to obtain a testing model on the test data.
6. Model Evaluation and Accuracy Comparison
   The final stage is model evaluation and accuracy comparison. After passing the test stage and producing test data, each built model is evaluated using the test data with evaluation metrics. These three methods are compared to determine which method is most effective in analyzing sentiment in Pinterest application reviews.

E. System Design

The fifth and final stage is system design. The system design section will contain an overview of the system to be created, such as usecase diagram, activity diagram, sequence diagram, and class diagram. A usecase diagram is a description of the collaboration between the system and the user. A use case diagram is used to explain the steps of the system to be created. An activity diagram is a visualization of work activities within the system or business processes and is part of the software. This diagram is depicted as a series of activity flows for both use cases and business processes. A sequence diagram is a tool used to describe and explain interactions between various entities in a system with detailed depth. Additionally, this diagram also shows the messages or instructions sent along with their execution times. The entities involved in the operational process are usually arranged from left to right. A class diagram is a diagram that depicts the static structure of a system. This diagram serves to visualize the classes within the system, including the attributes they possess, the methods available, and the relationships between objects. visualizing the structure of a programming system is the main purpose of a class diagram. Furthermore, class diagrams also have various other functions, such as showing the static structure of classifications within the system and providing basic notation for other structural diagrams that are needed.

F. Research Results Stage

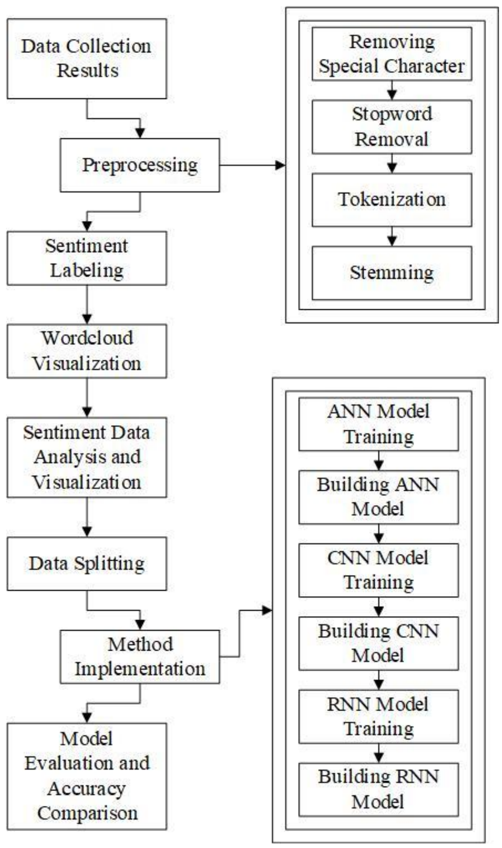


FIG 2. Result Research Stage

At this stage, an explanation will be provided regarding what is included in the research results section.

1. Data Collection Results
   This section contains the code for collecting user review data from the Pinterest application, resulting in a CSV file.
2. Preprocessing
   This section includes four requirements for the data to be processed: removing special characters, stopword removal, tokenization, and stemming. This part contains the code and results from the cleaned data.
3. Sentiment Labeling
   This section contains the code to add sentiment in the form of numbers: 1 (positive), -1 (negative), and 0 (neutral), with the assessment benchmark being a score/star rating.
4. Wordcloud Visualization
   This section contains the code and results in the form of visualizations of data for each sentiment.
5. Sentiment Data Analysis and Visualization
   This section contains the code and analysis of the sentiment data, divided into three points: sentiment distribution, value comparison, and data frequency.
6. Data Splitting
   This section contains the code to separate the training data and testing data, as the data will be used for model training and testing.
7. Method Implementation
   This section includes six sequences to proceed to the final part. The sequences that must be followed include training the ANN model, building the ANN model, training the CNN model, building the CNN model, training the RNN model, and building the RNN model. This part contains the code to train the methods used.
8. Model Evaluation and Accuracy Comparison
   This section contains the code and results from testing the data that will be evaluated using the models previously created. After the results are found, each method is compared to determine which has the highest accuracy.

3. Results And Discussion

A. Data Collection Results

The initial stage of the research process is data collection. In this research, data collection is carried out using a Google Play scraper tool integrated with Google Colab. The Google Play scraper is a Python library that allows for the automatic retrieval of reviews from applications available on the Google Playstore platform. By using this library, the researcher can collect user reviews of the Pinterest application for further analysis. The result of the data collection is a dataset in CSV format named pinterest_reviews_.csv, which contains user reviews of the Pinterest application. This dataset includes various important information, such as review text, star ratings, and user IDs relevant for sentiment analysis. A total of 20,000 reviews were successfully collected, in accordance with the specified parameters. This data will be used in the subsequent analysis stages, including preprocessing, sentiment labeling, and the application of deep learning methods (ANN, CNN, and RNN) to compare the accuracy of sentiment analysis.

B. Preprocessing

The next stage is data preprocessing. The data currently available has a disjointed format because during the data collection process, there is a high possibility of inaccuracies. Often, the data obtained contains duplicates and some entries are in languages other than Indonesian. Therefore, the existing data is transformed into a more structured format before implementing the methods. Preprocessing is divided into four steps: removing special characters, stopwords removal, tokenization, and stemming.

Removing special characters is one of the processes in text preprocessing aimed at eliminating elements such as symbols, numbers, or punctuation that are irrelevant to the analysis objectives. Special characters like @, #, %, or emojis often do not contribute significantly to sentiment analysis, so their removal can help simplify the data to be processed. The image 3 below shows the results of this stage.

Stopwords removal is the process of eliminating stopwords—words that frequently appear in text but do not contribute significantly to the understanding of the context or overall meaning. Examples of stopwords include words like "that," "and," "in," "from," and so on in English. The presence of stopwords can add complexity to the data without providing relevant information for analysis. The image 4 below shows the results of this stage.

Tokenization is the process of reducing sentences to a smaller form by breaking them up, these can be short phrases or words. This step aims to facilitate text data analysis by transforming the sentence format into a more organized data structure. Thus, the analysis process can be conducted in a more systematic manner. The image 5 below shows the results of this stage:

	User ID	Review	Bintang
0	Bang Cen	ini pinterest bagus tapi waktu lagi scroll scr...	3
1	Orang Bijak	apl ini udah sangat membantu dan fitur fitur y...	5
2	Hasna D. Pramesti	secara keseluruhan memang aplikasi ini sudah b...	5
3	Dhavina Syafa Velisya	pinterest kenapa tiba banget keluar dari akun ...	1
4	William Ramdani	secara keseluruhan aplikasi ini sudah sangat b...	4
5	Bila Nrean	pinterest knp sih aku pas login kagak bisa apa...	3
6	Miyo Sasaki	sangat bagus sekali algoritmanya juga mantap s...	5
7	Laila Sindy	tolong bisa tidak kalau setelah mengunduh gamb...	4
8	Rizqia Dwi Tasya Vinnindya	aplikasi ini udah baguss dan recommended bange...	4
9	phantom •	tambahkan fitur video singkat dan bisa di save...	5

FIG 3. Table Of Results For Removing Special Character

	User ID	Review	Bintang
0	Bang Cen	pinterest bagus waktu scroll scroll nyari setu...	3
1	Orang Bijak	apl udah sangat membantu fitur fitur lumayan b...	5
2	Hasna D. Pramesti	keseluruhan memang aplikasi sudah bagus mungki...	5
3	Dhavina Syafa Velisya	pinterest tiba banget keluar akun mau masuk ga...	1
4	William Ramdani	keseluruhan aplikasi sudah sangat bagus banyak...	4
5	Bila Nrean	pinterest knp sih aku pas login kagak apalagi ...	3
6	Miyo Sasaki	sangat bagus sekali algoritmanya mantap scroll...	5
7	Laila Sindy	kalau mengunduh gambar jangan menampilkan opsi...	4
8	Rizqia Dwi Tasya Vinnindya	aplikasi udah baguss recommended banget cari r...	4
9	phantom •	tambahkan fitur video singkat bisa savedownloa...	5

FIG 4. Table Of Results For Stopwords Removal

Stemming is a technique for simplifying words by converting them to their base form or root. This process aims to reduce the variation of word forms that have the same meaning, such as changing "bermain" (to play) to "main" (play). Thus, the text data becomes more consistent and can be managed more efficiently during the analysis process. The image 6 below shows the results of this stage:

	Review
0	[pinterest, bagus, waktu, scroll, scroll, nyar...
1	[udah, sangat, membantu, fitur, fitur, lumayan...
2	[keseluruhan, memang, aplikasi, sudah, bagus, ...
3	[pinterest, tiba, banget, keluar, akun, masuk,...
4	[keseluruhan, aplikasi, sudah, sangat, bagus, ...
5	[pinterest, login, kagak, apalagi, ngisi, tang...
6	[sangat, bagus, sekali, algoritmanya, mantap, ...
7	[kalau, mengunduh, gambar, jangan, menampilkan...
8	[aplikasi, udah, baguss, recommended, banget, ...
9	[tambahkan, fitur, video, singkat, bisa, saved...

FIG 5. Table Of Results For Tokenization

	Review
0	[pinterest, bagus, waktu, scroll, scroll, nyar...
1	[udah, sangat, bantu, fitur, fitur, lumayan, b...
2	[seluruh, memang, aplikasi, sudah, bagus, mung...
3	[pinterest, tiba, banget, keluar, akun, masuk,...
4	[seluruh, aplikasi, sudah, sangat, bagus, bany...
5	[pinterest, login, kagak, apalagi, ngisi, tang...
6	[sangat, bagus, sekali, algoritmanya, mantap, ...
7	[kalau, unduh, gambar, jangan, tampil, opsi, b...
8	[aplikasi, udah, baguss, recommended, banget, ...
9	[tambah, fitur, video, singkat, bisa, savedown...

FIG 6. Table Of Results For Stemming

If the preprocessing stage has been completed, then combine the data tables to produce an image like the one below:

	User ID	Review	Bintang	final_review
0	Bang Cen	pinterest bagus waktu scroll scroll nyari setu...	3	pinterest bagus waktu scroll scroll nyari setu...
1	Orang Bijak	udah sangat membantu fitur fitur lumayan banya...	5	udah sangat bantu fitur fitur lumayan banyak s...
2	Hasna D. Pramesti	keseluruhan memang aplikasi sudah bagus mungki...	5	seluruh memang aplikasi sudah bagus mungkin ta...
3	Dhavina Syafa Velisya	pinterest tiba banget keluar akun masuk gabisa...	1	pinterest tiba banget keluar akun masuk gabisa...
4	William Ramdani	keseluruhan aplikasi sudah sangat bagus banyak...	4	seluruh aplikasi sudah sangat bagus banyak ora...
5	Bila Nrean	pinterest login kagak apalagi ngisi tanggal la...	3	pinterest login kagak apalagi ngisi tanggal la...
6	Miyo Sasaki	sangat bagus sekali algoritmanya mantap scroll...	5	sangat bagus sekali algoritmanya mantap scroll...
7	Laila Sindy	kalau mengunduh gambar jangan menampilkan opsi...	4	kalau unduh gambar jangan tampil opsi bagi kon...
8	Rizqia Dwi Tasya Vinnindya	aplikasi udah baguss recommended banget cari r...	4	aplikasi udah baguss recommended banget cari r...
9	phantom •	tambahkan fitur video singkat bisa savedownloa...	5	tambah fitur video singkat bisa savedownload p...

FIG 7. Merged Results

	User ID	Review	Bintang	final_review	Sentimen
0	Bang Cen	pinterest bagus waktu scroll scroll nyari setu...	3	pinterest bagus waktu scroll scroll nyari setu...	0
1	Orang Bijak	udah sangat membantu fitur fitur lumayan banya...	5	udah sangat bantu fitur fitur lumayan banyak s...	1
2	Hasna D. Pramesti	keseluruhan memang aplikasi sudah bagus mungki...	5	seluruh memang aplikasi sudah bagus mungkin ta...	1
3	Dhavina Syafa Velisya	pinterest tiba banget keluar akun masuk gabisa...	1	pinterest tiba banget keluar akun masuk gabisa...	-1
4	William Ramdani	keseluruhan aplikasi sudah sangat bagus banyak...	4	seluruh aplikasi sudah sangat bagus banyak ora...	1
5	Bila Nrean	pinterest login kagak apalagi ngisi tanggal la...	3	pinterest login kagak apalagi ngisi tanggal la...	0
6	Miyo Sasaki	sangat bagus sekali algoritmanya mantap scroll...	5	sangat bagus sekali algoritmanya mantap scroll...	1
7	Laila Sindy	kalau mengunduh gambar jangan menampilkan opsi...	4	kalau unduh gambar jangan tampil opsi bagi kon...	1
8	Rizqia Dwi Tasya Vinnindya	aplikasi udah baguss recommended banget cari r...	4	aplikasi udah baguss recommended banget cari r...	1
9	phantom •	tambahkan fitur video singkat bisa savedownloa...	5	tambah fitur video singkat bisa savedownload p...	1

FIG 8. Sentiment Labeling Result

C. Sentiment Labeling

After the data has been successfully cleaned using several preprocessing techniques, sentiment labeling will be performed. The sentiment labeling process is conducted to assign sentiment categories to each review in the dataset[18]. Higher scores, such as 4 or 5, are considered positive reviews, while lower scores, such as 1 or 2, are regarded as negative reviews. A score of 3, which is in the middle, is considered neutral. This approach ensures that each review is clearly categorized based on user perception. The image below shows the results of this stage:

D. Wordcloud Visualization

After performing sentiment labeling, a visualization of the words used will be created, specifically a word cloud. A word cloud is a data visualization technique used to display the words that frequently appear in a collection of text. The more often a word is used, the larger its size in the word cloud. In this sentiment analysis[19], the word cloud is used to identify the dominant words in positive, neutral, and negative reviews. Below is the image of the overall word visualization, as well as the visualizations for positive, neutral, and negative words:

FIG 9. Overall Wordcloud Visualization

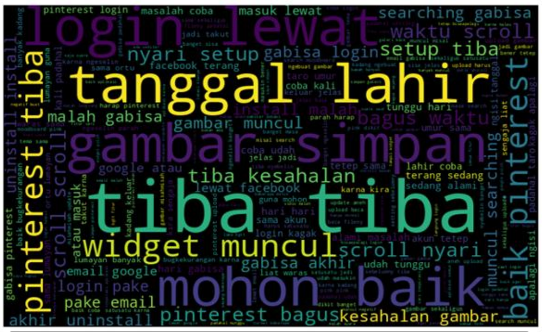


FIG 10. Netral Wordcloud Visualization

FIG 11. Positive Wordcloud Visualization

FIG 12. Negative Wordcloud Visualization

E. Sentiment Data Analysis and Visualization

After creating the word cloud visualization, the next step will be to analyze and visualize the sentiment data that has been collected and labeled with positive, negative, and neutral sentiments. Data visualization plays a crucial role in facilitating the understanding and analysis of the reviews expressed by Pinterest application users[20]. The sentiment data visualization will be presented in the form of a bar chart. There are three points that can be analyzed and visualized from the sentiment data that has been collected. The first is the analysis and visualization of sentiment distribution. Sentiment distribution explains the number of reviews that fall into each sentiment category.

Once the bar chart is displayed, the number of reviews will be shown at the bottom, and the sentiment categories will be shown on the side. With a total data count of 20,000, there are 11,200 entries classified as positive sentiment, 2,800 entries classified as neutral sentiment, and 6,000 entries classified as negative sentiment. It can be concluded that the majority of Pinterest application users provide positive sentiment in their reviews, indicating a relatively high level of satisfaction. This is the visualization of the sentiment distribution:

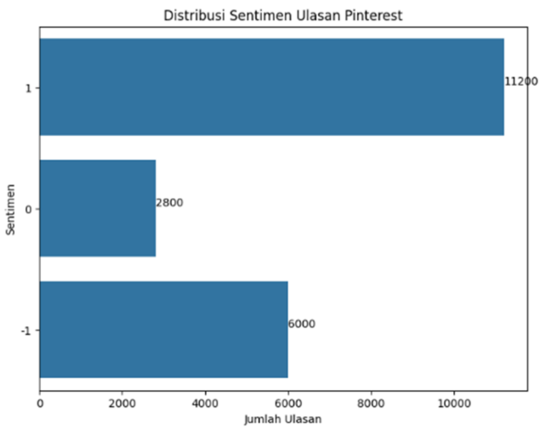


FIG 13. Sentiment Distribution Visualization

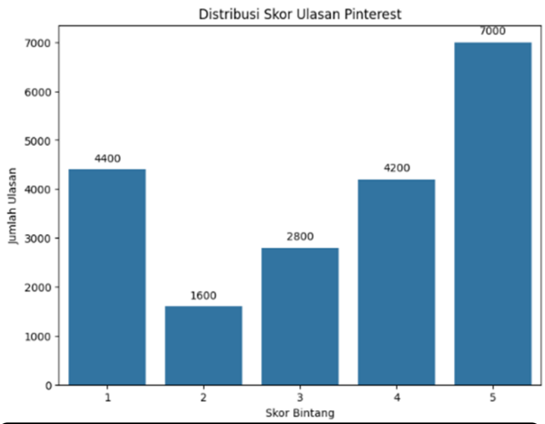


FIG 14. Rating Comparison Visualization

The second point is the analysis and visualization of rating comparisons. The rating comparison explains the number of reviews given for each rating using a scale from 1 to 5 as the standard rating.

Once the bar chart is displayed, the scores/stars will be shown at the bottom, and the number of reviews will be shown on the side. With a total data count of 20,000, there are 4,400 entries classified with a score/star of 1, 1,600 entries classified with a score/star of 2, 2,800 entries classified with a score/star of 3, 4,200 entries classified with a score/star of 4, and 7,000 entries classified with a score/star of 5. It can be concluded that the rating with a score/star of 5 is the highest, indicating that the majority of Pinterest application users provide positive sentiment in their reviews and show a positive outlook towards the Pinterest application. This is the visualization of the rating comparison in Fig. 14.

The third point is word frequency. Word frequency explains the words that appear most frequently in this sentiment data.

Once the bar chart is displayed, the top 10 words in the sentiment data will be shown on the left, and the frequency of each word will be displayed at the bottom. In the top three positions, the word "gambar" (image) ranks number 1 with a frequency of 14,000 occurrences, followed by the word "bagus" (good) at number 2 with a frequency of 10,800 occurrences, and the word "aplikasi" (application) at number 3 with a frequency of 10,400 occurrences. It can be concluded that users frequently use the word "gambar" when writing reviews for the Pinterest application, whether in positive or negative reviews. This is the visualization of word frequency:

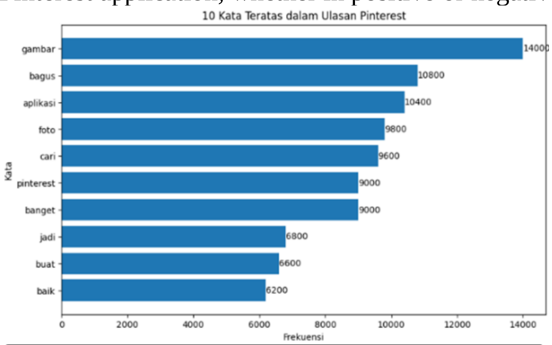


FIG 15. Data Frequency Visualization

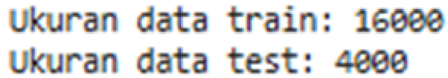


FIG 16. Results Of Data Splitting

FIG 17. Results Of Training The ANN Model

F. *Data splitting*

Next is the data splitting stage. After the sentiment labeling process is completed, the data will be divided into two parts: training data and testing data[21]. In this stage, the data labeled as positive, negative, and neutral will be separated into two main sections: training data (train) and testing data (test). The data is split into these two sections with a ratio of 80:20, where 80% of the data is used for training and 20% for testing. The results will be displayed as shown in fig. 16

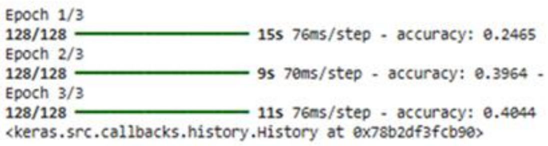
G. *Method Implementation*

Then we move on to the implementation stage of the methods. In this stage, three commonly used deep learning algorithms for sentiment analysis are implemented: ANN, CNN, and RNN. Each model is trained using the previously processed dataset, with the aim of comparing the performance of each method in classifying customer review sentiments.

Artificial Neural Network (ANN) is a model of artificial neural networks that consists of several layers of neurons. This model is designed to recognize patterns in data and make decisions based on weights that are updated during the training process[22]. In sentiment analysis, ANN is used to identify patterns of relationships between words in the reviews and the sentiment labels assigned. After the data is prepared, the architecture of the ANN model is built with several main layers. The data type is first converted to numeric because the ANN model operates with numerical data. The batch size (the number of data samples processed) and the number of epochs (the number of training iterations) are determined to create the model[23]. The results displayed will look like the fig. 17

Convolutional Neural Network (CNN) is a model that was originally developed for image analysis but can also be applied to text processing[24]. CNN works by extracting important features from text data using convolution operations, allowing the model to capture recurring patterns in customer reviews. The code to be included for training the model consists of the installation of libraries, importing modules, the approach used, and data splitting. After the data is prepared, the architecture of the CNN model is built with several main layers. The data type is first converted to numeric because the CNN model operates with numerical data[25]. The batch size (the number of data samples processed) and the number of epochs (the number of training iterations) are determined to create the model. The results displayed will look like the fig. 18

Recurrent Neural Network (RNN) is a deep learning model designed to handle sequential data, such as text. RNN is chosen because it is a method that is compatible with large data and is capable of remembering information from previous steps. This model is capable of recognizing relationships between words in a sentence because it has an internal memory mechanism that can store information from previous words[26]. The code to be included for training the model consists of the installation of libraries, importing modules, the approach used, and data splitting. After the data is prepared, the architecture of the RNN model is built with several main layers. The data type is first converted to numeric because the ANN model operates with numerical data. The batch size (the number of data samples processed) and the number of epochs (the number of training iterations) are determined to create the model[27]. The results displayed will look like the fig. 19



```
Epoch 1/3
128/128 ━━━━━━━━━━━━━━━━━━━━ 15s 76ms/step - accuracy: 0.2465
Epoch 2/3
128/128 ━━━━━━━━━━━━━━━━━━━━ 9s 70ms/step - accuracy: 0.3964 -
Epoch 3/3
128/128 ━━━━━━━━━━━━━━━━━━━━ 11s 76ms/step - accuracy: 0.4044
<keras.src.callbacks.history.History at 0x78b2df3fcb90>
```

FIG 18. Results Of Training The CNN Model

```
Epoch 1/3
128/128 ━━━━━━━━━━━━━━━━━━━━ 44s 291ms/step - accuracy: 0.3167 -
Epoch 2/3
128/128 ━━━━━━━━━━━━━━━━━━━━ 38s 301ms/step - accuracy: 0.6464 -
Epoch 3/3
128/128 ━━━━━━━━━━━━━━━━━━━━ 39s 286ms/step - accuracy: 0.6351 -
<keras.src.callbacks.history.History at 0x78b2db0025d0>
```

FIG 19. Results Of Training The RNN Model

H. Model Evaluation and Accuracy Comparison

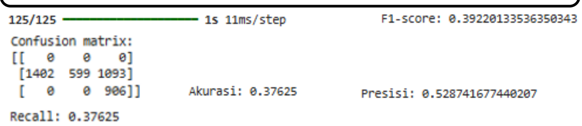
The final stage is model evaluation. This evaluation aims to measure how well the ANN, CNN, and RNN models recognize text patterns and accurately determine sentiment[28]. Several metrics used in the model evaluation are:

1. F1-score: Provides an accurate picture of model performance by balancing the total prediction results[29].
2. Confusion Matrix: Resulting in the total number of correct and incorrect predictions[30].
3. Accuracy (Accuracy Score): Measures how often the model makes correct predictions compared to the total number of test data.
4. Precision (Precision Score): The model produces a total of positive predictions, so what is calculated is the actual ratio.
5. Recall (Recall Score): Measures how many samples from a particular sentiment class were correctly identified.

The image below shows the results of the data testing and the evaluation of the model for each method:

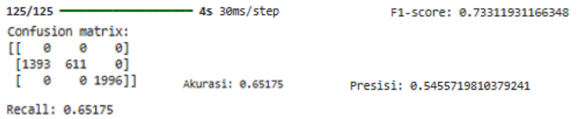
```
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step          F1-score: 0.2914829128866811
Confusion matrix:
[[   0    0    0]
 [1374  591 1602]
 [   0    0  433]]      Akurasi: 0.256          Presisi: 0.5332300252312868
Recall: 0.256
```

FIG 20. Results Of Testing and Evaluating The ANN Model



```
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step          F1-score: 0.39220133536350343
Confusion matrix:
[[   0    0    0]
 [1402  599 1093]
 [   0    0  906]]      Akurasi: 0.37625          Presisi: 0.528741677440207
Recall: 0.37625
```

FIG 21. Results Of Testing and Evaluating The CNN Model



```
125/125 ━━━━━━━━━━━━━━━━━━━━ 4s 30ms/step          F1-score: 0.73311931166348
Confusion matrix:
[[   0    0    0]
 [1393  611    0]
 [   0    0 1996]]      Akurasi: 0.65175          Presisi: 0.5455719810379241
Recall: 0.65175
```

FIG 22. Results Of Testing and Evaluating The RNN Model

Based on the testing and evaluation results of the three deep learning methods (ANN, CNN, RNN), it can be analyzed that the ANN model shows low performance with an accuracy of only 25.6% (0.256) from the test data totaling 4,000.

The F1-score of the ANN model is only 0.2914, which is considered low, indicating that the ANN model lacks balance in classifying positive and negative sentiments. The higher precision value of 0.5332 indicates that when the model predicts positive, the likelihood of that prediction being correct is better. However, the low recall value of 0.256 shows that many positive sentiments are not detected.

Next, the CNN model shows better performance than the ANN model with an accuracy of 37.63% (0.3763) from the test data totaling 4,000. The F1-score, which is better than that of the ANN model at 0.3922, demonstrating that the CNN model is more balanced in classifying positive and negative sentiments. The precision (0.5287) and recall (0.37625) values being close together make the CNN model better at detecting positive predictions compared to the ANN model.

Lastly, the RNN model shows the best performance among the three models, achieving an accuracy of 65.17% (0.6517) from the test data totaling 4,000. The high F1-score of 0.7331 making this model effective in classifying positive and negative sentiments. The precision (0.5458) and recall (0.65175) values, which are higher than those of the ANN and CNN models, indicate that the RNN model is better at detecting positive predictions and has a low error rate.

6. CONCLUSIONS

Based on the results, can be concluded that data from the Google Playstore provides valuable insights into public opinion regarding the Pinterest application, with complaints related to performance issues such as difficulties in downloading images and irrelevant ads, which can affect user satisfaction. These reviews can be used for application improvements.

From the sentiment data that has been analyzed, including sentiment distribution points, value comparisons, and word frequency, the majority of Pinterest application users express positive sentiment in their reviews, indicating a relatively high level of satisfaction. The high positive ratings reflect a favorable view of the Pinterest application. Additionally, the frequently occurring words predominantly reflect the key features and benefits perceived by Pinterest application users.

The RNN method shows the highest accuracy in sentiment analysis, reaching 65.17%, followed by CNN (37.63%) and ANN (25.6%). RNN also has the highest F1-score (0.7331), demonstrating its effectiveness in classifying data. The analysis results indicate that the developed system is adequate for performing sentiment analysis on the Pinterest application.

However, sentiment analysis of Pinterest app user reviews using ANN, CNN, and RNN methods still has limitations. Suggestions for further development from this research include exploring other methods in sentiment analysis, such as the BERT algorithm or more advanced deep learning techniques, to improve classification accuracy. Additionally, expanding the data from other platforms or using larger and more diverse datasets to gain a broader perspective on sentiment towards the Pinterest application is recommended.

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