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Sentiment Analysis of Twitter Reviews on Google Play Store Using a Combination of Convolutional Neural Network and Long Short-Term Memory Algorithms

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Abstract

In this era of rapidly evolving technology, the use of social media has become widespread and has become a major platform for sharinhabibahdian.khalifah@ogr.deu.edu.trg people's opinions and views. Google Play Store, as one of the main platforms for digital content, provides access to various applications including Twitter, which allows users to provide reviews and ratings. This research aims to conduct sentiment analysis of Twitter reviews on the Google Play Store using two algorithms namely Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). The data used is 4999 reviews after the scraping process. From the experimental results, an accuracy value of 84.67%, recall of 81%, and precision of 84% were obtained on CNN, and an accuracy of 82.19% recall of 69%, and precision of 87% on LSTM. From these results, it can be seen that the highabibahdian.khalifah@ogr.deu.edu.trhest accuracy value is obtained in the CNN algorithm. Although the difference in accuracy is small, the CNN algorithm provides better results in classifying sentiment analysis data on Twitter reviews on the Google Play Store.

Keywords: Convolutional Neural Network, Google Play Store, Long Short-Term Memory, Sentiment Analysis

1. INTRODUCTION

Rapid technological advances, especially in the field of social media, are widely used by the public to convey opinions and express their views [1]. The popularity of social media has become an effective means to influence others and convey opinions to the general public [2]. The number of social media enthusiasts today causes the amount of data generated to increase and is very large (big data). With big data technology, processing large, large, and complex data becomes easier, so that the processed data can provide useful information [3].

Google Play Store is a digital platform owned by Google that provides various digital products, including apps, music, books, games, media players, and other services [4]. Twitter was chosen as the object of study because it is one of the most popular social media in the world, with features that allow users to voice opinions on various topics. The platform, founded by Jack Dorsey in 2006, has more than 237 million daily active users and was profitable in the second quarter of 2022 [5]. This study aims to understand the relationship between user reviews and sustained app popularity, with a focus on user perceptions, satisfaction trends, and development opportunities to improve competitiveness in the digital marketplace. Twitter was analyzed through the Ratings and Feedback feature on the Google Play Store, where users can rate (1-5) and comment on their experience. As of June 2024, the Twitter app has received an average rating of 4.7 [6]. The lower star rating value indicates that the application performance is less than optimal when used by users [6]. This research is focused on evaluating user opinions on the Google Play Store for the Twitter app. Lately, the Twitter application on the Play Store has received many negative reviews, because many users complain that accessing photos and videos is very slow, and many accounts are suddenly suspended. From these problems, an evaluation can be carried out, one of which is by analyzing sentiments on user opinions on the Google Play Store for the Twitter app.

The use of sentiment analysis, especially on the social media platform Twitter, aims to identify relevant moods or opinions contained in tweets on a particular topic. This is done by categorizing the text into specific sentiment categories (positive or negative) based on the context and tone of the language used [7]. Sentiment analysis is also often called Opinion analysis or Opinion mining [8]. In the ever-changing world of smart devices, understanding user sentiment has become critical to perfecting technology and improving user experience [9]. The importance of Sentiment Analysis was raised in this study because user reviews on platforms such as Google Play Store have a huge impact on public perception and the decision to use an app. A combination of Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM) algorithms was chosen as CNN excels in extracting important features from text data, while LSTM is effective in capturing the context of data sequences. The combination is expected to improve accuracy in identifying positive and negative sentiments from user reviews. This analysis not only helps app developers understand user needs and concerns but also provides valuable insights for marketing strategies and service quality improvement.

In this work, the sentiment of Shopee application reviews on the Google Play Store was analyzed using the Naive Bayes method, building on earlier research on sentiment analysis of user evaluations [3]. Various data-sharing methods are used to do this. The results showed that the HoldOut data-sharing technique with a ratio of 80:20 resulted in an algorithm accuracy of 83%, 1% higher than the average result of the 10-Cross Fold Validation data-sharing technique that produced an accuracy of 82% [3]. Furthermore, Priyadarshini and Cotton's research from 2021 examined fundamental algorithms like CNN, LSTM, K-nearest neighbors, convolutional neural networks, and LSTM-CNN. Several datasets have been used to test the LSTM algorithm utilizing F-1 ratings for specificity, sensitivity, accuracy, precision, and sensitivity. As compared to other basic models, the findings obtained indicate that the suggested model, which relies on hyperparameter optimization, has an accuracy of over 96% [10]. Another study by Muhammad et al., (2021), This study uses the LSTM and Word2Vec models, with a combination of parameters that produces the best accuracy of 85.96% on a dataset of 2500 review texts. The parameter combinations for Word2Vec are Skip-gram architecture, Hierarchical Softmax evaluation method, and 300 vector dimensions, while for LSTM are a dropout value of 0.2, average pooling, and learning rate 0.001 [11].

Previous research has met the standard in using various methods and algorithms for sentiment analysis, such as Naive Bayes, LSTM, and Word2Vec. However, this research offers novelty by focusing on sentiment analysis of Twitter app reviews on Google Play Store using a combination of CNN and LSTM algorithms. This combination has not been widely applied in research related to sentiment analysis of application reviews, especially for social media platforms such as Twitter. The advantage of using CNN lies in its ability to extract important features from text, while LSTM excels in capturing temporal relationships and context in word sequences. This research aims to improve the accuracy in identifying positive and negative sentiments by combining the two algorithms, which is expected to provide more optimal results compared to previous studies using a single algorithm.

This research will employ Google Collaboratory tools in conjunction with CNN and LSTM algorithms to do sentiment analysis on social media applications like Twitter. The use of CNN and LSTM algorithms in conjunction with sentiment analysis is what makes this research so urgent. This is a new approach compared to previous studies that generally only use one of the two algorithms. This combination is expected to overcome the limitations of each algorithm in understanding the context and important features of the review text data. As such, this research offers improved accuracy and effectiveness When classifying user evaluations on the Google Play Store based on emotion, which has not previously been achieved with conventional methods. This could significantly advance the field of sentiment analysis and aid in the creation of applications that are more receptive to user input. It is anticipated that this research will also reveal information regarding the attitude expressed by users of the app in their reviews.

2. MATERIAL AND METHOD

CNN and LSTM are used in this study. algorithms to analyze the sentiment of user reviews that are extracted from Twitter and posted on the Google Play Store. As a result, as illustrated in Figure 1, researchers will conduct numerous phases of study to learn more about and contrast the three algorithms' performances.

2.1. Stage of Research

2.1.1. Scraping Web

Web scraping allows researchers to extract data from various sites to combine in a single spreadsheet or database, easing data analysis. This is particularly beneficial in machine learning research to obtain large datasets from various sources, which are used to train and test models [12].

2.1.2 Text Processing

The text processing process involves three main stages. The first stage is text cleaning, where the text is cleaned of punctuation, numbers, URLs, mentions, and hashtags to remove irrelevant information. The second stage is tokenization, which breaks the text into tokens or individual words[13]. For example, the sentence "I like Python" becomes ["I", "like", "Python"]. The third stage is stemming, converting words into basic forms, such as converting "running", "running around", and "run" into "run". This process prepares the text data for further analysis, such as sentiment analysis to identify emotions or opinions in the text.

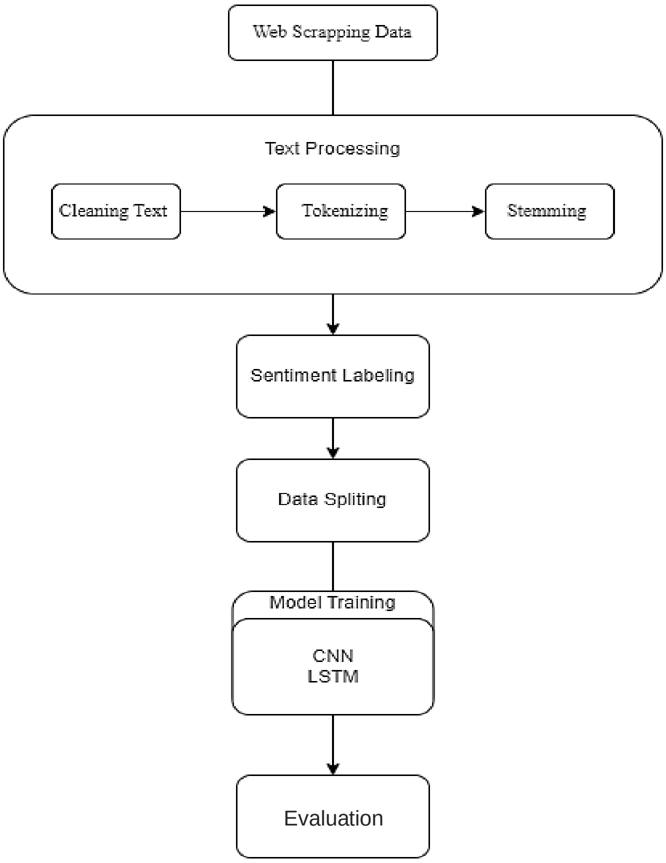

Figure 1. Research Methodology

2.1.3 Sentiment Labeling

Sentiment labeling is important in sentiment analysis, by labeling text based on emotions such as positive, negative, or neutral. This process is crucial for training machine learning models to accurately recognize sentiment patterns. Labeled data allows evaluation of model performance through methods such as accuracy and precision, helping to identify model strengths and weaknesses. Sentiment labeling also supports trend analysis in product reviews, sentiment change detection, and personalization of user experience on digital platforms.

2.1.4 Splitting Data

A crucial machine learning technique is data splitting, which divides the dataset into testing and training data for the model's performance evaluation. Preventing overfitting and assessing the model's generalizability to fresh data are the objectives [14]. By splitting the dataset, we can objectively measure the predictive ability of the model, essential for the development of effective and reliable machine learning models.

2.1.5 Training Model

The model training process with LSTM and CNN starts with the CNN layer to extract features from the input data (such as text or images). These features are then passed to the LSTM layer to process the temporal relationships in the data sequence. The model is updated through iterations to optimize performance, using training data and a specified loss function. The result is a model that is ready to be used for prediction or classification based on new input [15].

2.1.6 Evaluation

To assess the performance of a classification model, model evaluation is essential. Commonly used metrics include accuracy, precision, recall, and F1 score. Accuracy measures the number of correctly classified instances; values close to 100% indicate a good model, while precision measures the proportion of truly positive events. The F1 score indicates that precision and recall are balanced [16].

2.1. Google Collabs

Google Collab, a cloud computing platform owned by Google, has become a popular choice for researchers and practitioners working to develop and teach deep learning and machine learning models. To improve the performance and reduce the inference time of testing, training, and testing have been done on the multi-core GPU provided by Google Collab [17]. However, while using the free version, users often face time and resource constraints. Google offers two premium subscription levels, Collab Pro and Collab Pro+, to address this issue. To help users understand the advantages and disadvantages of each subscription level, an overview of Collab Pro and Collab Pro+ is given here [18].

2.2. Sentiment Analysis

One of the most often used text-based analytics applications is sentiment analysis, which is used to mine people's attitudes, feelings, views, and judgments regarding various situations, entities, subjects, events, and products. Sorting the retrieved data into sentiment polarities—such as positive, neutral, and negative—is the essential step in implementing sentiment analysis [19]. Sentiment analysis is currently widely used in many fields, including business, finance, politics, education, and law. It is not only used by researchers; it is also used by governments, organizations, and businesses [20]. Multimodal sentiment analysis is the process of analyzing data from audio or audio-visual devices, such as webcams, to look at expressions, gestures, or voices. Sentiment analysis is often done on text data. Multimodal sentiment analysis increases the complexity of text-based analysis, creating new opportunities for the application of NLP [21].

2.3. Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM)

In recent years, deep learning models (CNNs) have achieved remarkable results in image recognition. CNNs train models to classify images based on visual features by extracting important patterns from a series of convolution and pooling layers, then using multiple fully connected layers to generate class probability scores [22]. The learned feature map shows that CNN is very good at utilizing local correlations and patterns in the data, and in some text classification tasks, the embedding of various words in a sentence (or paragraph) is often stacked to create a two-dimensional array [23]. Next, a length-varying convolution filter is applied to generate a new feature representation in the word window. To form the hidden representation, the combined features of the various filters are merged. Then, a merge operation often maximum merge is used on the new features. One or more layers are fully connected [24].

LSTM is a deep learning technique used for text data prediction, sentiment analysis, language modeling, and speech analysis. LSTM can handle text data with long-term dependencies [25].The LSTM Network is a kind of RNN that solves disappearing and exploding gradient issues. Three gating techniques are used by LSTMs: input, forget, and output gates. Information enters through the input gate, information exits through the forget gate, and information entering the system is gated by the output gate. This allows the error gradient to flow during backpropagation without being lost [26]. Three gates (input, output, and forget) and a memory cell control the information that enters and exits the LSTM architecture. Additionally, the cell retains values for arbitrarily long periods.

The CNNs and LSTMs share a fundamental similarity in their learning methods, in that they are both deep learning models designed to learn patterns or features from complex data. Both use gradient-based approaches, such as backpropagation, to optimize model parameters during the training process [27]. Although CNNs are more often applied to spatially correlated data, such as images, and LSTMs to sequential data, such as text or audio, their main goal remains the same, which is to extract significant features relevant to a particular task, be it classification, prediction, or analysis [28].

3. RESULTS AND DISCUSSION

3.1. Web Scraping

Through Google Collaboratory and the Python programming language, web scraping of Twitter links on the Google Play Store was performed, resulting in 4999 recent review data in 2024. The scraping process involves the installation of the Google Play-scraper library, where it is only necessary to enter the application ID of the available links to access the reviews.

3.2. Text Preprocessing

Text preprocessing is an essential initial step in sentiment analysis to clean and prepare textual data before applying it to analytical models. This stage aims to improve data quality, ensuring that sentiment analysis results are more accurate and relevant. In the results and analysis section of a scientific paper, text preprocessing is often described to demonstrate its impact on model performance. Before implementing the classification algorithm, a preprocessing step is carried out which is useful for cleaning the review text [29]. The following are the preprocessing steps.

3.3. Term Frequency-Inverse Document Frequency (TF-IDF)

TF-IDF is a statistical method used to evaluate the importance of a word in a document relative to a collection of documents (corpus). In text analysis, TF-IDF is often used to represent textual data in numerical form so it can be utilized in machine learning models or further analysis.

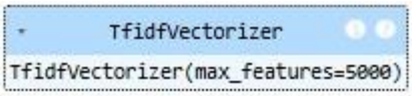

Figure 2 TF-IDF Result

The result of the fit process on the TfidfVectorizer object is the formation of a mathematical representation of the text based on the TF-IDF value. This process analyzes the text of the given training data (in this case the Text column of data_text) to calculate the TF-IDF value of each word that appears. In this case, the number of unique words considered is limited to 5000 words with the highest value according to the parameter max_features = 5000. The TF-IDF results can be seen in Figure 2.

3.4. Sentiment Labelling

This stage is to recognize and classify sentiments expressed in text, such as whether the sentiment is positive or negative from Twitter reviews on the Play Store where the value <3 is considered negative, while >=3 is considered positive. Sentiment labeling classification was successfully carried out into 2 groups, namely 446 negative sentiments and 350 positive sentiments can be seen in Table 5. Figure 3 illustrates the results of sentiment identification, indicating that out of 398 user reviews for the Twitter app on the Google Play Store, 2227 reviews belong to positive sentiment classes and 2773 to negative sentiment classes.

Table 5. Sentiment Labeling

	User Name	Sentiment	Time	Text	Label
0	Pengguna Google	Negatif	2024-06-14 14:04:05	parah aplnya bug g masuk	0
1	Pengguna Google	Negatif	2024-06-13 14:08:57	return tab like w tf ayo ramai review kembali ...	0
2	Pengguna Google	Negatif	2024-06-12 02:58:20	harga premium mahal fasilitas jelek banget cha...	0
3	Pengguna Google	Positif	2024-06-12 02:42:13	bagus iklan	1
4	Pengguna Google	Negatif	2024-06-12 02:19:08	bad	0

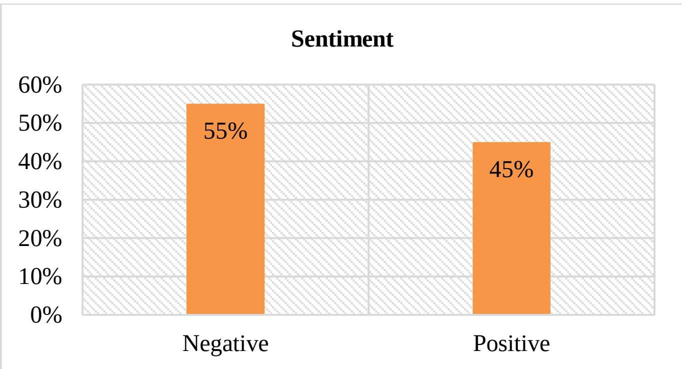

Figure 3 Sentiment Result

3.5. Evaluation of Classification CNN dan LSTM

The evaluation stage, which comes after, looks at the Class Precision and Class Recall values that were produced throughout the classification process using the LSTM and CNN algorithms.

3.4.1 Convolutional Neural Network (CNN)

Using the Google Collab dataset described above, CNN and LSTM classification algorithms were applied. The CNN classification model used is Conv1D, RMSprop optimizer, and epoch size of 25. The goal is to calculate the loss and loss values based on the confusion matrix, the data used for training, and validation data. The visualization results of the CNN algorithm obtained a loss value of 37.83% and an accuracy of 84.67% Figure 3 shows the visualization results of the accuracy and loss of the CNN algorithm.

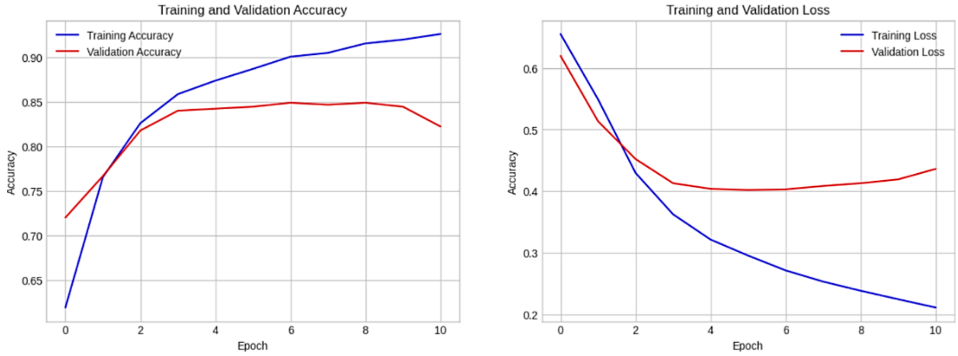

Figure 3 CNN Visualization Results

3.4.2 Long Short-Term Memory (LSTM)

In the LSTM classification model used is the RMSprop optimizer, and the epoch size is 25. The goal is to calculate the value of loss and loss based on the confusion matrix, the data used for training, and data validation. Visualization results of the LSTM algorithm obtained a loss value of 43.04% and an accuracy of 82.19% Figure 4 shows the visualization results of the accuracy and loss of the LSTM algorithm.

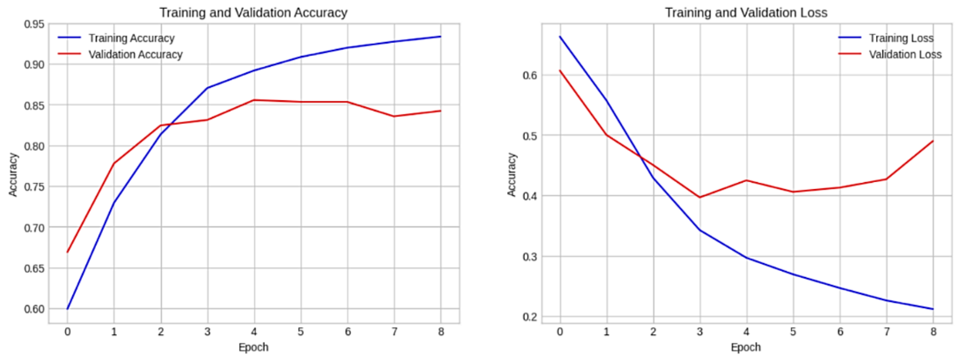

Figure 4 LSTM Visualization Results

According to the sentiment classification results with CNN and LSTM modeling shown above, the CNN algorithm produces the best classification results on Twitter App User Reviews on Google Play Store. This shows that the LSTM model is better at minimizing prediction errors compared to LSTM. In addition, the accuracy of CNN is also slightly higher, which is 84.67%, compared to the accuracy of LSTM which reaches 82.19%. Although the difference is small, CNN still shows superiority in both evaluation matrices. Overall, although the performance of the two algorithms is very similar, CNN provides better results in terms of accuracy and prediction error rate.

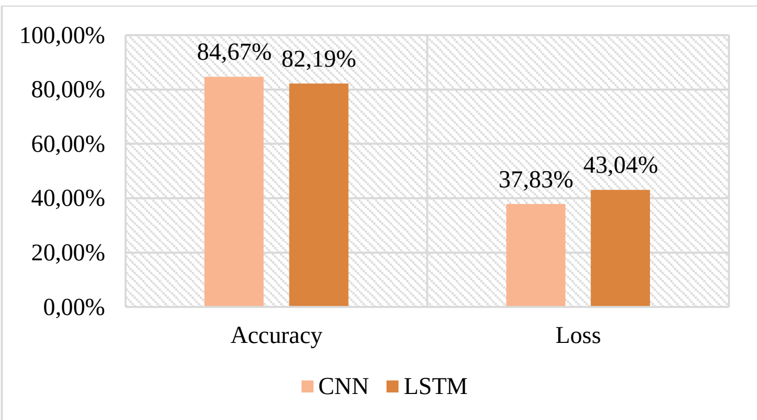

Figure 5 Comparison of Classification Algorithms

3.4.3 WordCloud

The analysis of word cloud sentiment analysis on Figure 6 is a visual representation of the most frequent words in reviews with positive sentiment from Twitter apps. This Word Cloud makes it easy to identify words that are frequently used in positive reviews. The greater the word's size, the more frequently it appears. Some of the words that stand out include "good", "app", "great", "account", and "Twitter", showing users frequently mentioning the app's quality, functionality, user account, and brand name. Words like "good", "great", "cool" and "good" indicate positive user experiences, while words like "please" and "bugs" indicate areas that need improvement. Overall, this Word Cloud provides a quick visual summary of the positive aspects of Twitter apps according to users and can be used by developers and marketers to understand and improve features that users value.

Figure 7 displays the negative sentiment towards an app, with larger words indicating a higher frequency of occurrence. The words "app", "account", "login" and "register" appear frequently, indicating many complaints about access and registration difficulties. Words such as "difficulty", "error", "bug", and "error" indicate frequent technical problems. Other terms such as "update", "open", "loading", and "sign in" indicate specific difficulties in using the app. The word "Twitter" also appears, indicating many complaints related to the platform. This word cloud provides a visual depiction of the various issues and user dissatisfaction with the app.

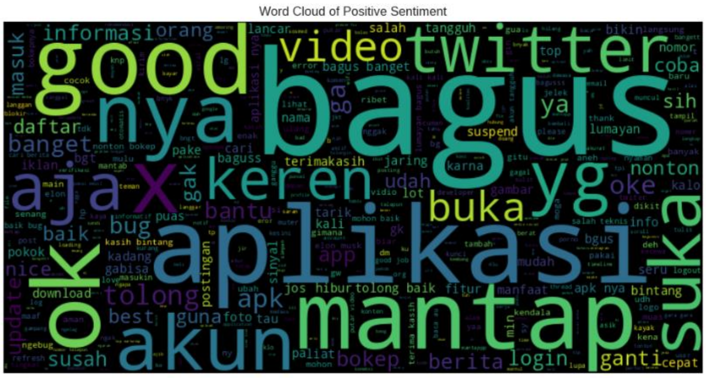

Figure 6 Positive Word Cloud

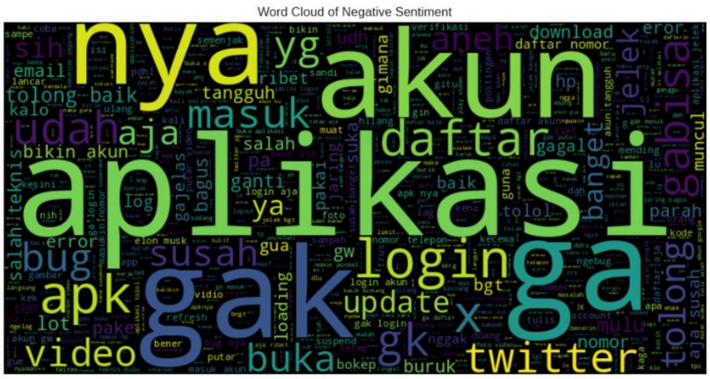

Figure 7 Negative Word Cloud

4. CONCLUSION

This research analyzes the sentiment of Twitter user reviews on Google Play Store using CNN and LSTM algorithms.The results show that CNN is superior with 84.67% accuracy compared to LSTM (82.19%).Although the difference in accuracy is small, CNN is more effective in recognizing review data patterns.This research has several weaknesses, such as the limited number of datasets, the unexplored modern models such as BERT, and the lack of optimization of model parameters. In addition, the classification only uses positive and negative categories, thus ignoring more complex contexts. Future research can be improved by expanding the dataset, using newer models such as BERT, performing parameter optimization, adding neutral sentiment classification, and applying aspect analysis to understand the specific aspects that influence reviews. This is expected to provide more optimized and comprehensive results.

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