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Sentiment Analysis of User Reviews of Mutual Fund Investment Applications on Google Playstore using Long Short Term Memory (LSTM) Algorithm

Nurlaela*, Teguh Iman Hermanto, Dede Irmayanti

Department of Informatics, Sekolah Tinggi Teknologi Wastukancana, Purwakart, Indonesia
Email: [1*]nurlaelanurlaela68@wastukancana.ac.id, [2]teguhiman@wastukancana.ac.id, [3]dedeirmayanti@wastkancana.ac.id
Email Penulis Korespondensi: nurlaelanurlaela68@wastukancana.ac.id

Abstract−Mutual fund investment is increasing, as evidenced by the increasing number of mutual fund application users on the Playstore platform in Indonesia. The Financial Services Authority (OJK) reported that the number of mutual funds in Indonesia until August 2022 reached 2,193 units. In this research, the data collection used is the data scrapping method on the Google Playstore website. The result of the scrapping data is an excel-formatted document of 3000 data which is then stored and processed using the Long Short Term Memory (LSTM) model. In order to facilitate the modeling stage later, the sentiment review data must go through a text preprocessing process. To improve the performance and performance of LSTM modeling more optimally, then in this study a choice of hyperparameters was made. The hyperparameters tested are Epoch, Batch Size and Layer LSTM. The highest accuracy value on the Ajaib dataset is 99.3% which is located at epoch 32 and batch size 50, the highest accuracy value on the Bareksa dataset is 95.1% which is located at epoch 32 and batch size 50, and the highest accuracy value on the Bibit dataset is 94.9% which is located at epoch and batch size 50. So that the highest accuracy value among the three datasets is obtained by the Ajaib dataset where the accuracy reaches 99.3%. From the test results of the three parameters, it proves that there is an increase in accuracy results that is good enough to reach the highest accuracy value of 0.9933.

Keywords: Mutual Fund; Investment Applications; Google Playstore; Sentiment Analysis; LSTM

1. INTRODUCTION

Financial literacy is increasing and growing rapidly in this digital era, raising public awareness of the importance of investing. Investment is an activity of allocating assets within a certain period of time in order to obtain profits in the future. Investment is one of the alternative ways to achieve financial freedom[1]. Referring to the results of the Katadata Insight Center (KIC) review during September 6-12, 2021, it is stated that the application that is in great demand is Bibit, which is a mutual fund investment application. The results of the examination reported that 71.9% of the interviewees used the Bibit application for their investment needs. Bareksa was the second most used app at 22.8%. The majority of respondents, 75.6%, also admitted to buying mutual funds on online applications. Then 24.1% of respondents bought through e-wallets, and as many as 18.4% through marketplaces and another 10.5% through banks. Ajaib is the most widely used stock investment platform in Indonesia. There are 35.5% of total respondents who claim to use Ajaib for their stock investment. Gen Z is the main user of Ajaib with 41% of respondents. Then Gen Y at 34.1% and Gen X & Boomers at 31%. With the current online investment, it will certainly make it easier for investors to invest. This online investment is quite practical because it can easily access investment offering sites or applications. However, this online investment is only based on a sense of trust from each related party, online investment through sites or applications may cause problems that sometimes lack insight and vigilance of investors, especially beginners to finance and capital markets[2].

Google Playstore is an android market platform in which there is a review and rating feature of various applications. Applications that have been downloaded on the Playstore platform can be given comments and ratings by the user. The rating starts from 1 to 5[3]. However, there are some irregularities in reviews on the Google Play Store where a user gives a small rating such as one or two stars, but the text review provided is a positive feedback or the user gives a high rating but the text review provided has a negative value. As a result, Google cannot can't distinguish positive reviews from negative reviews through the review text provided by users and can affect the actual rating of the app. affect the actual rating of the app[4]. Sentiment analysis can classify opinion sentences in the form of positive, negative, and neutral sentences. So that it can produce information for entities both companies and agencies[5]. Sentiment analysis is the examination of an opinion or someone's opinion on a topic. The basic task of sentiment analysis is classify some text from documents, sentences or features, sentences from features can be positive, negative and neutral. Can be positive, negative and neutral. In performing sentiment analysis a method that supports the classification is needed[6].

The Long Short Term Memory (LSTM) algorithm is another type of Recurrent Neural Network (RNN) construction that is generally used in cases related to deep learning. Research using LSTM has been done, one of which is about the problem of hate speech, which is specific to 2019 about the presidential election[7]. The accuracy value obtained in this study with the LSTM method was higher, reaching 77% compared to the naive bayes method whose accuracy only reached 76%[8]. The results obtained from this research are that the LSTM method has better performance when compared to Naïve Bayes. The LSTM method produces accuracy, precision and recall values of 83.33%. While the Naïve Bayes method has an accuracy, precision and recall value of 82%[9]. An accuracy value of 97% and a loss of 12% were obtained based on the test results using the LSTM method[10]. The model used in this research is the Long Short Term memory (LSTM) model which produces a fairly good accuracy of 88%[11]. This research produces an accuracy value of 91.08% using the LSTM method, which from the results of its evaluation, the teaching method of a lecturer can be improved[12]. Previous research related to sentiment analysis using the LSTM algorithm is research on sentiment analysis of 2019 covid vaccine tweets, which from the test results poured the results of RNN (TF-IDF) has a greater accuracy of 97.77% compared to Naïve Bayes (TF-IDF) of 80%[13]. In his research, he stated that the performance of the LSTM model combined with Word2Vec representation is better than other basic models[14].

2. RESEARCH METHODOLOGY

2.1 Research Stages

In this study using the Long Short Term Memory (LSTM) algorithm, the following Figure 1 is the research stages.

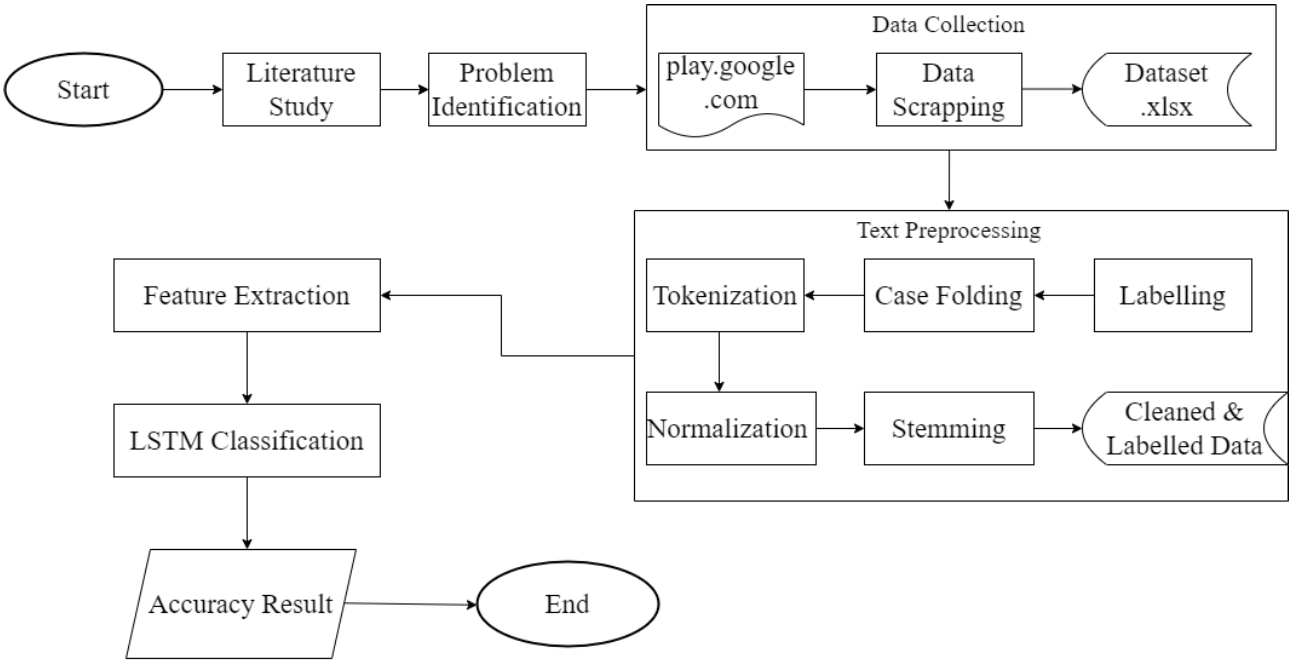


Figure 1. Research Stages

In Figure (1), the stages in the research methodology are explained, starting from literature study, problem identification, data collection, text preprocessing, then through the feature extraction stage, then classification using the LSTM algorithm and finally the accuracy results of LSTM which is an evaluation.

2.2 Literature Study

At this stage, the main step is to search for and read various references in the form of journals and research reports that have previously existed that have relevance to the topic to be discussed, namely sentiment analysis and research using the *Long Short Term Memory* (LSTM) algorithm and research conducted based on user reviews of applications on Google Playstore.

2.3 Problem Identification

The data collection process carried out in this study is the Application Website Scrapping method on Google Playstore using Google Extension, which results from Scrapping Data in the form of documents in format.xlsx. The source of this research data comes from the Playstore Website. An official application store website for the Android operating system which also includes a review column of various existing applications. Data is taken by scrapping "newest", "highest rating", and "lowest rating". In this study, researchers focused on the results of scrapping data in the "highest rating" and "lowest rating" ratings to get positive and negative sentiment results. In this process, the tools used are from Google Extension. The Google Playstore website has 4 review rating categories, namely: "newest", "oldest", "highest rating" and "lowest rating". In this study, researchers focused on scrapping the "highest rating" and "lowest rating" data to get positive and negative sentiment results. The results of 3000 scrapping data are obtained, namely Ajaib 1000 data, Bareksa 1000 data and Bibit 1000 data. The process of data collection can be seen in Figure 1 below.

2.4 Data Collection

After collecting and studying references, the next step that must be taken is to identify problems related to data related to this research, where the data comes from the application on Google Playstore. Google Playstore is a digital distribution service as the official application store for the Android operating system, developed and operated by Google. In this study, 3 mutual fund investment applications were selected on the Google Playstore platform, namely Ajaib, Bareksa, and Bibit. The 3 applications were chosen based on the best mutual fund recommendations for beginners released by katadata.co.id infographics that the three applications were widely discussed by netizens on social media platforms such as Twitter and Instagram. Then the next stage is planning the necessary data collection or data scrapping that will be researched.

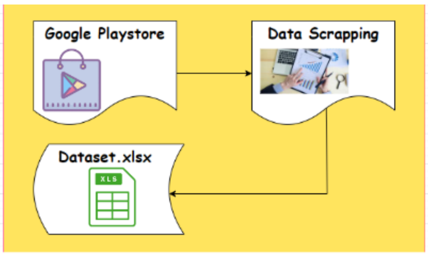


Figure 2. Data Collection

In Figure (2) above, we can see the flow of the data collection process. The data collection process begins with accessing the Google Playstore website which is then scrapped data on user reviews of recdadana applications on the Google Playstore website which includes 3 applications namely Ajaib, Bareksa and Ajaib. Then the data that has been scrapped is in the form of Dataset.xlsx format.

2.5 Text Preprocessing

After the data is collected, the next stage that must be done is the text preprocessing process. In this text preprocessing stage, several processes are carried out including Labelling, Case Folding, Tokenization, Normalization and Stemming. In the Labelling stage, the stored dataset will be labeled using Microsoft Excel. The labels used are divided into two groups, namely negative and positive. The labelling process is done using Microsoft Excel. In this stage, it is divided into 2 types of sentiment, namely negative reviews and positive reviews which aim to determine the accuracy level of the classification prediction results[15]. Case Folding is the process of converting all text data into lowercase letters to minimize case sensitive[16]. In an analysis, tokenization is a necessary step before the text is processed. In this Tokenization, the sentences in a text will be decapitated into words, which is useful for minimizing the confusion of the meaning of the text[17]. In this normalization process, the spelling of words that are commonly used in general is done[18]. In Stemming, the sentences in the dataset will be returned to their basic word form, which removes the prefix and suffix from each word, to make it easier to observe and understand the meaning of each word[19]. The process of text preprocessing can be seen in Figure 1 below.

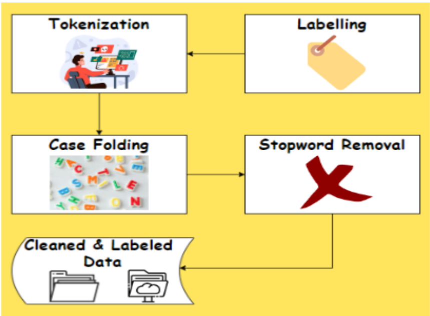


Figure 3. Text Preprocessing

In Figure (3) above is an overview of the text preprocessing process. In the picture, the text preprocessing process above starts with dataset labeling, tokenization, case folding, and stopword removal. After going through the text preprocessing stage, we will get a clean and labeled dataset that is ready to be processed to the next stage.

2.6 Feature Extaction

The next feature extraction process uses the Word2Vec Model. Where in the use of this Word2Vec Model, comments in the dataset in the form of text that has been divided into words will be converted into a vector value, which is of course averaged with a total of 100 features[20]. During the classification process, the comment feature will be represented by the result of the average value of the vector[21].

2.6 LSTM Classification

Long Short Term Memory (LSTM) is an algorithm that has the advantage of estimating an approximate model[22]. Problems that cannot be solved by RNN, it is appropriate to use LSTM as an alternative way to solve the problem[23]. Long Short Term Memory (LSTM) is one part of the Deep Learning algorithm that utilizes cell-memory blocks consisting of input gate, forget gate, and output gate. Forget gate is the main gate in LSTM, where in this process information sorting is done. Next, the information that has been sorted will pass through the second door in LSTM, namely the Input gate which has 2 sigmoid layers. Then the output cell state will be determined when it has passed through the output gate layer[24]. The LSTM architecture can be seen in figure 4 below.

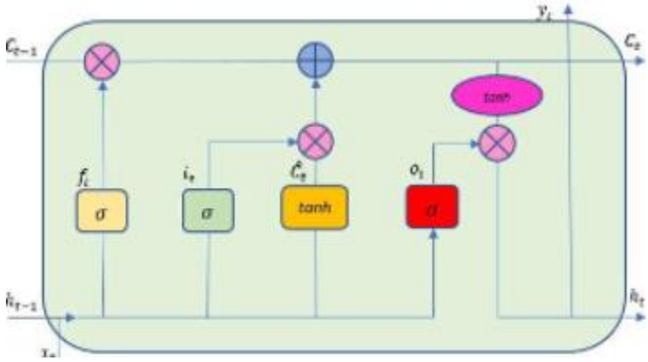


Figure 4. Architecture of LSTM

In Figure (4) of the LSTM architecture above, each line carries an entire vector, from the output of one node to the input of another. The pink circles represent element operations, such as addition or multiplication of vector elements, while the yellow squares are layers of the neural network (containing parameters and biases) that can learn. Two joined lines signify the merging of two matrices/vectors, while a split line signifies the content is copied and the copy goes to a different node.

3. RESULT AND DISCUSSION

In this research, there are several parameters used in LSTM modeling, namely testing based on epoch, batch size and LSTM layer. From the third parameter testing experiment it can improve the performance of a better and optimal LSTM model. The following are the results of parameter testing.

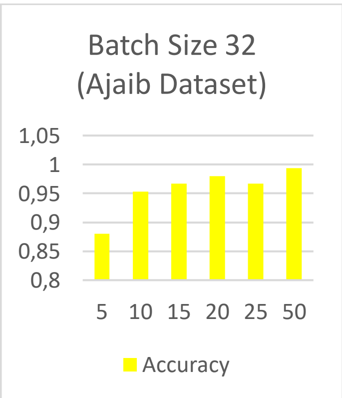
3.1 The result of LSTM Model with different Epoch and Batch Size

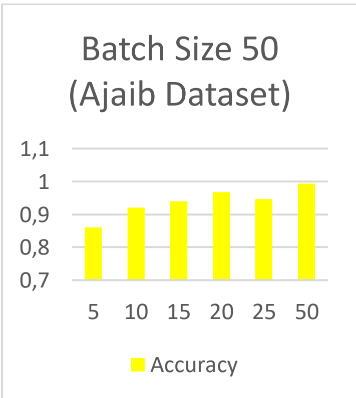
Based on the test results attached to the following figures (5) and tables (1), testing on the Ajaib dataset is carried out by comparing epochs and batch sizes where the epochs used are 5, 10, 15, 20, 25, and 50, while the batch sizes are 32, 50, 64, 128 and 256 with LSTM layer 4. The test results show that the highest accuracy value on the Ajaib dataset is 99.3%, where the highest accuracy value is obtained at an epoch value of 32 and batch size 50.

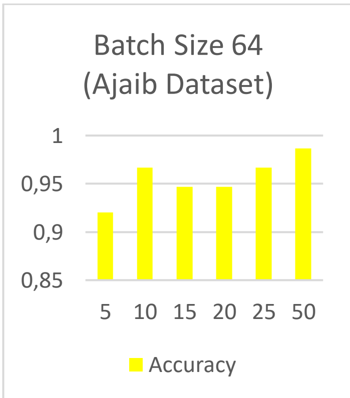
Table 1. Batch Size + Epoch Comparation

Ajaib Dataset Using 32, 50, 64, 128, 256 of Batch Size & Layer LSTM (4)					
Batch Size\ Epoch	*32*	*50*	*64*	*128*	*256*
5	0,9497	0,8237	0,8237	0,9	0,840
10	0,9533	0,8608	0,8608	0,9333	0,8467
15	0,9667	0,9095	0,9095	0,940	0,9067
20	0,98	0,9281	0,9281	0,9467	0,9333
25	0,9667	0,9327	0,9327	0,9467	0,9067
50	**0,9933**	0,9513	0,9513	0,9733	0,960

In table (1) above, shows the results of the Batch Size and Epoch Comparison testing experiments on the Ajaib dataset where from the comparison it can be seen that the highest accuracy value is in the Epoch 32 trial with a Batch Size of 50 of 0,9933.







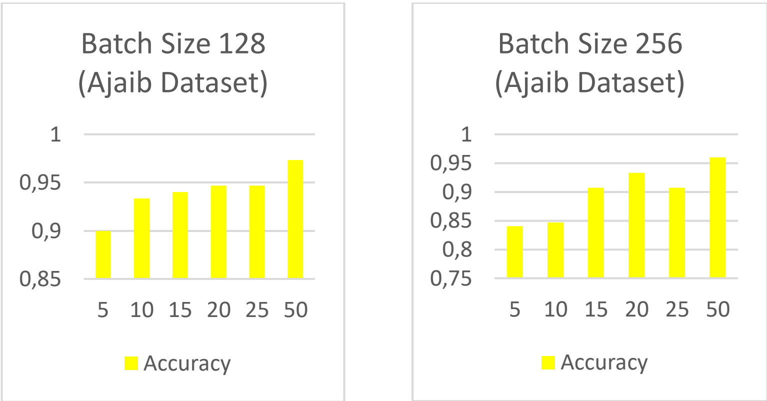


Figure 5. An accuracy result of LSTM model on Ajaib dataset

In Figure (5) above, displays the results of the Batch Size and Epoch Comparison testing experiments on the Ajaib dataset into a diagram whose data is linked to the Ajaib Dataset table.

Table 2. Batch Size + Epoch Comparation

Bareksa Dataset Using 32, 50, 64, 128, 256 of Batch Size & Layer LSTM (4)					
Batch Size\ Epoch	32	50	64	128	256
5	0,8237	0,7935	0,8144	0,7685	0,7819
10	0,8608	0,8376	0,8886	0,8097	0,7796
15	0,9095	0,891	0,8724	0,8144	0,8051
20	0,9281	0,9118	0,9002	0,8701	0,7912
25	0,9327	0,9211	0,9188	0,8886	0,8283
50	**0,9513**	0,9443	0,9490	0,9258	0,8817

In the experiments conducted above table (2), the Bareksa dataset was tested using LSTM layer 4 and epoch values of 5, 10, 15, 20, 25 and 50 with batch sizes of 32, 50, 64, 126 and 256. The highest accuracy result is found in the comparison of epoch 50 with batch size 32 with LSTM layer 4 where the accuracy value on the Bareksa dataset is 0,9513.

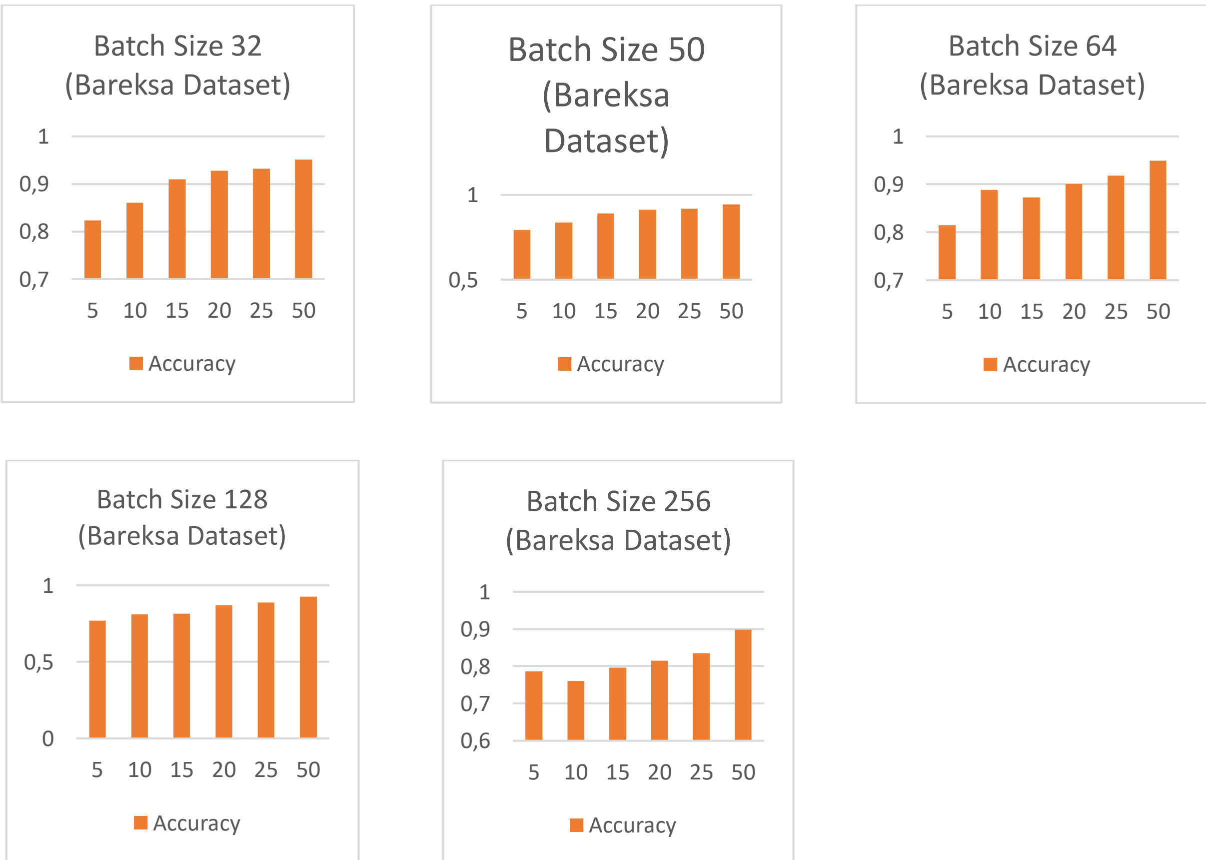


Figure 6. An accuracy result of LSTM model on Bareksa dataset

In Figure (6) above, displays the results of the Batch Size and Epoch Comparison testing experiments on the Bareksa dataset into a diagram whose data is linked to the Bareksa Dataset table.

Table 3. Batch Size + Epoch Comparation

Bibit Dataset Using 32, 50, 64, 128, 256 of Batch Size & Layer LSTM (4)					
Batch Size\ Epoch	32	50	64	128	256
5	0,7961	0,743	0,8144	0,7011	0,6844
10	0,905	0,8855	0,8886	0,757	0,7123
15	0,9162	0,8939	0,8724	0,8701	0,7318
20	0,9413	0,9246	0,9002	0,8771	0,7402
25	0,9441	0,9413	0,9188	0,9106	0,8547
50	**0,9497**	0,9443	0,9490	0,9413	0,9134

Above are table (3) of test results on LSTM layer 4 using epoch comparison values of 5, 10, 15, 20, 25 and 50 as well as batch sizes of 32, 50, 64, 128 and 256. From these results it can be concluded that with an epoch value of 32 and batch size 50 it produces the greatest accuracy value compared to others, the greatest accuracy value is 0,9497.

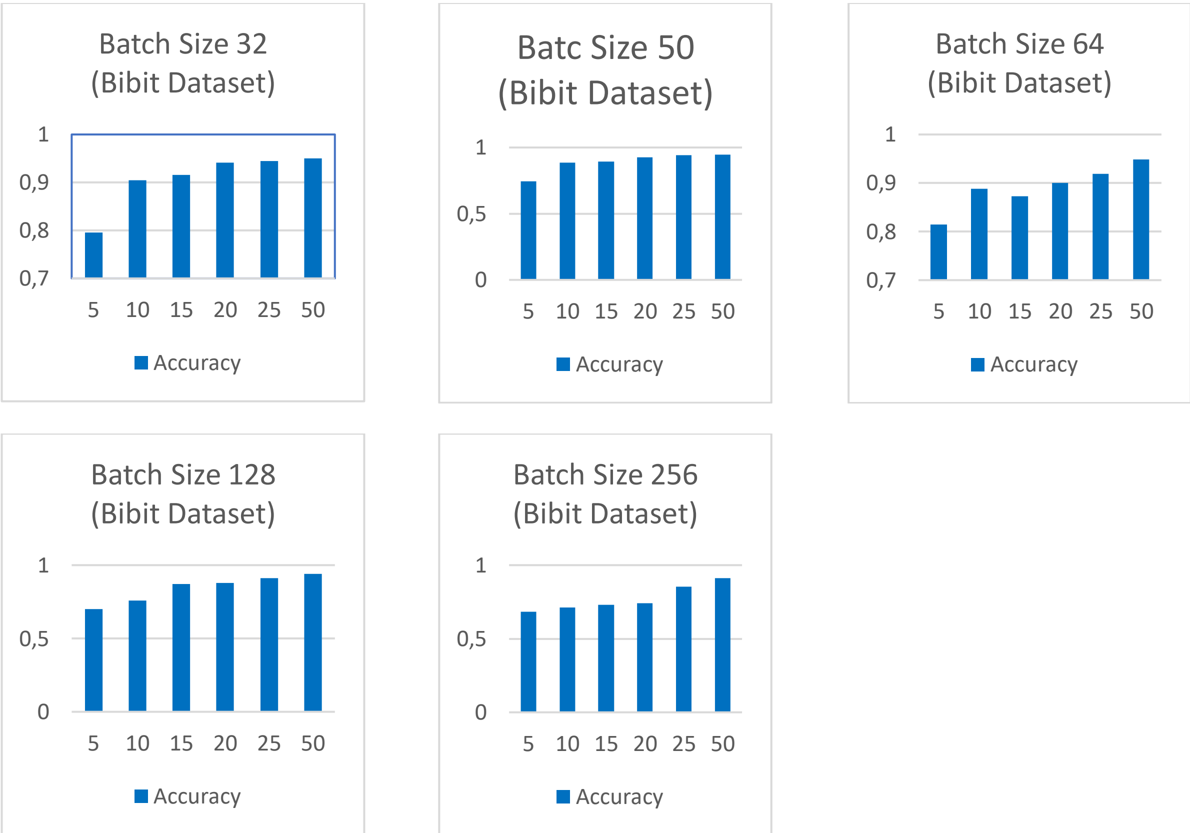


Figure 7. An accuracy result of LSTM model on Bibit dataset

In Figure (7) above, displays the results of the Batch Size and Epoch Comparison testing experiments on the Bibit dataset into a diagram whose data is linked to the Bibit Dataset table.

From the three tables it can be concluded that the comparison of epoch and batch size with LSTM layer 4, the best accuracy result value is obtained from each dataset attached, namely the Ajaib, Bareksa and Ajaib datasets. The highest accuracy value on the Ajaib dataset is 99.3% which is located at epoch 32 and batch size 50, the highest accuracy value on the Bareksa dataset is 95.1% which is located at epoch 32 and batch size 50, and the highest accuracy value on the Seedling dataset is 94.9% which is located at epoch and batch size 50. So the highest accuracy value among the three datasets is obtained by the Ajaib dataset where the accuracy reaches 99.3%.

3.2 Test results of LSTM Model with LSTM Layer Comparation

After comparing epochs and batch sizes on the same lstm layer, namely 4 layers, the best accuracy results were obtained from the tested epochs (5,10,15,20,25, and 50) and batch size trials (32, 50, 64, 128, and 256). Based on the comparison experiment, the most optimal epoch and batch size with LSTM layer 4 is epoch 50 with batch size 32 which is able to achieve an accuracy value of 0,9497. Based on the experimental results with the dataset used from the Bibit sentiment product on the playstore platform, it turns out that the greater the epoch, the accuracy value will increase or increase while the greater the batch size used, the accuracy value will decrease or decrease, so both are very influential on the accuracy value of LSTM.

Table 4. LSTM Layer Comparation

Using Epoch 50 & Layer LSTM (4)	
Batch Size	*Accuracy*
32	**0,9497**
50	0,9441
64	0,949
128	0,9413
256	0,9134

Above is table (4) of test results on the comparison of LSTM layer 4 and epoch 50 using batch sizes 32, 50, 64, 128 and 256. From these results it can be concluded that the highest accuracy value is at batch size 32.

Table 5. LSTM Layer Comparation

Using Epoch 50 & Layer LSTM (8)	
Batch Size	*Accuracy*
32	0,9525
50	0,9469
64	**0,9553**
128	0,9497
256	0,9333

In the table (5) from the results of the epoch, batch size and LSTM layer comparison experiments on the Seedlings dataset, there are two parameters that greatly affect the accuracy value of the LSTM model, namely epoch determination and batch size, which are then optimized by using the best LSTM layer. Now in this trial, the best comparison is obtained at layer LSTM 8 with epoch 50 and batch size 64 with the highest accuracy of 0.9553.

4. CONCLUSION

The best level of accuracy from the results of research that has been done using the Long Short Term Memory (LSTM) model is to achieve an accuracy value of 0.9933 obtained on Ajaib products using a combination of epoch value 50 batch size 32 and 4 LSTM layers. It is recommended that for future research, it is necessary to experiment with various techniques and hyperparameters to find the optimal combination and improve model accuracy.

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