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Effect of Epoch Value on the Performance of the RNN-LSTM Algorithm in Classifying Lazada App Review Sentiments

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Abstract: This research examines attitudes towards the Lazada application. The main objective of this study is to determine the sentiment towards the e-commerce company Lazada application. In the current development, the process of buying and selling transactions between sellers and buyers is growing. By utilising sentiment analysis, opinion gathering evaluates emotional expressions and text tendencies (positive and negative). Not only is it done directly but it can also be done online or can be called e-commerce. Which is where the rapid development of technology indirectly encourages entrepreneurs to develop through e-commerce. Lazada is one of the online stores in Indonesia that has many users and Lazada provides convenience in shopping without the need to come to the place or directly. However, purchasing goods using e-commerce has problems regarding the quality of the goods you want to buy, therefore purchasing goods can be seen through reviews of each item you want to buy. The purpose of this research is to assess the level of accuracy of sentiment analysis classification models using deep learning and neural networks. This research applies the Recurrent Neural Network (RNN) algorithm with Long Short Term Memory (LSTM). As well as using the Epoch value as a parameter in processing validation data and test data to be able to produce the best accuracy value. Experiments were conducted using training datasets, and testing was conducted using datasets from the Lazada website. The findings show that this model provides excellent results, reaching around 86.18%.

Keywords: e-commerce, Lazada, RNN, LSTM, Epoch

INTRODUCTION

The rapid advancement of technology has resulted in several transformations in consumer behaviour, especially in daily activities such as online shopping. E-commerce applications, such as Lazada, are now one of the main platforms that present a variety of products to fulfil consumer needs.

This research aims to conduct sentiment analysis of user reviews and feedback on the Lazada app. Through sentiment analysis, this research seeks to identify and understand the emotional tone and polarity of the text contained in user reviews. In addition, this research also adopts a deep learning approach, specifically using the Recurrent Neural Network (RNN) algorithm with Long Short Term Memory (LSTM), the aim of improving the accuracy of sentiment analysis.

E - commerce is an online marketplace and a method of conducting business that allows buyers and sellers to engage in transactions through the internet (Yin, 2022). Lazada is one of the few large e-commerce and already around 100 million users have downloaded the Lazada application (Ramadhan, 2022). Competition in the trading industry always continues. Therefore, sellers need to understand the factors that can improve or at least maintain their business by following current technological developments (Azizah, 2023). However, every purchase through the marketplace will begin with some consumer considerations by looking at reviews from consumers who have bought before (Rais et al., 2022). Reviews have a significant role for consumers, because they provide references that help them make decisions and get views from the personal experiences of individuals who have used the product or service before.

The features owned by Lazada E-commerce allow consumers who have made buying and selling transactions to provide an assessment of the products they buy (Anandyara & Samiono, 2022). The Lazada application is ranked fourth in e-commerce in Indonesia, where Lazada offers various types of products such as electronic goods, men's and women's clothing, various household appliances, health and beauty products, sports, travel, automotive and

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many sizes need to be analyzed per authority (Tirta Wiyata & Zaelani, 2021). To date, Lazada.co.id's success has been fuelled by an effective business communication strategy, enabling the penetration of the e-commerce market in geographically and culturally diverse Indonesia (Andriani & Prihantoro, 2022).

Sentiment analysis for product reviews, also known as text orientation analysis or opinion mining, refers to the process of automatically analyzing the text of subjective comments (Yang et al., 2020). Reviews will be categorized as positive if the information presented is positive and reflects satisfaction. Conversely, if the review presents unfavorable information or shows dissatisfaction and disapproval, it will be considered as negative.

The Recurrent Neural Network (RNN) method with Long Short Time Memory (LSTM) is one of the deep learning models that can be used to perform sentiment analysis (Cahyadi et al., 2020).

It is proposed to use the RNNLSTM method in Lazada sentiment classification and see the effect of using different epoch values on the accuracy of the model obtained. Epoch is used to determine how many rounds or literations need to be done when training the model in order to learn the patterns and trends in the data well. In practice, the optimal epoch can be found by experimenting on training data with various epoch values and selecting the value that gives the best results on validation or testing data. Therefore, choosing the right epoch is very important to achieve good performance in sentiment analysis.

LITERATURE REVIEW

Related Work

Several researchers have previously conducted sentiment analysis regarding e-commerce. In this study, they conducted sentiment analysis on BPJS using the RNN method (Faturohman, 2020). In this study, in comparing methods. The Recurrent Neural Network method achieved the best accuracy of 96% (Awaliyah Zuraiyah et al., 2023). And the use of the Epoch value is one of the parameters that can determine the best accuracy value (Jahidul Islam Razin et al., 2021).

Sentiment analysis involves studying how sentiments and viewpoints expressed in natural language are associated with emotions and attitudes concerning a particular occurrence or event (Yadav & Vishwakarma, 2020). Furthermore, in the next research, conduct sentiment analysis of the Shoope application using the Recurrent Neural Network (RNN) method. With the combination method of Smote and Tomek Link, to handle unbalanced data. By using this method it becomes better and balanced (Utami, 2022). From the results and performance of the sentiment analysis results for Shoope user data in Indonesia, the results and classification prediction accuracy rate are 80%, precision 84.4%, sensitivity 30% specificity, and F1-Score 88.1%.

In sentiment analysis research on social media using the LSTM method which in this study uses epoch parameters which are carried out 20 times. The results obtained show some potential accuracy of ternary data with a fairly good accuracy value on training data 98% and testing data 66%. And for the accuracy value of the average accuracy value is 89.45% (Astari & Wahib Rozaqi, 2021).

Based on the research results, for sentiment classification using hyperparameters, testing is carried out and the model can predict application reviews using the BiLSTM model using a hyperparameter of 16 neurons and the sixth epoch and produces an accuracy of 81% (Subowo, 2020.).

From the results of several studies above, sentiment analysis using the Recurrent Neural Network (RNN) method with the addition of epoch values can get quite good accuracy results and add balanced final results from the dataset used.

RNN

Recurrent Neural Network (RNN) became a well-known method for language modelling tasks, such as speech recognition, machine translation, and text generation. RNN was able to describe the sequence by capturing a temporal link between the elements in that order (Al Haromainy et al., 2023).

Recurrent Neural Networks (RNN) are capable of keeping a record of all input values that have been seen by the network, including the current input. The hidden values in each layer of the RNN network depend on all the inputs that have been previously processed in a particular order (Thomas & Latha, 2018). In this model, every sentence was initially introduced to the recursive neural network as a concealed layer, and subsequently, the associated vectors were treated as inputs to the recurrent neural network.

The classification using RNN possesses benefits in the process of data recognition, specifically having internal memory to retain crucial information (feedback loop) from preceding data, which is employed for making precise predictions.

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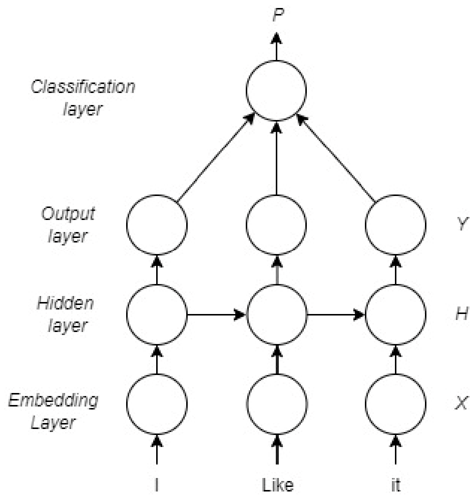

Fig. 1 Recurrent Neural Network(RNN)

LSTM

Long Short-Term Memory (LSTM) represents a specialized form of Recurrent Neural Network (RNN). Unlike traditional RNNs, which encounter challenges in learning long-term information due to issues like exploding and vanishing gradients, LSTM addresses this limitation effectively (Nurrohmat & SN, 2019). In LSTM, the conventional RNN node in the hidden layer is replaced with specialized LSTM cells. These cells are explicitly engineered to store and retain crucial information from previous steps, mitigating the problems associated with long-term information learning in standard RNNs.

METHOD

At the stage built this system performs sentiment analysis of Lazada e-commerce applications from several user reviews that have been selected based on positive and negative public responses using Term Frequency Inverse Document Frequency (TF-IDF) weighting and epoch value feature selection with the RNN-LSTM method.

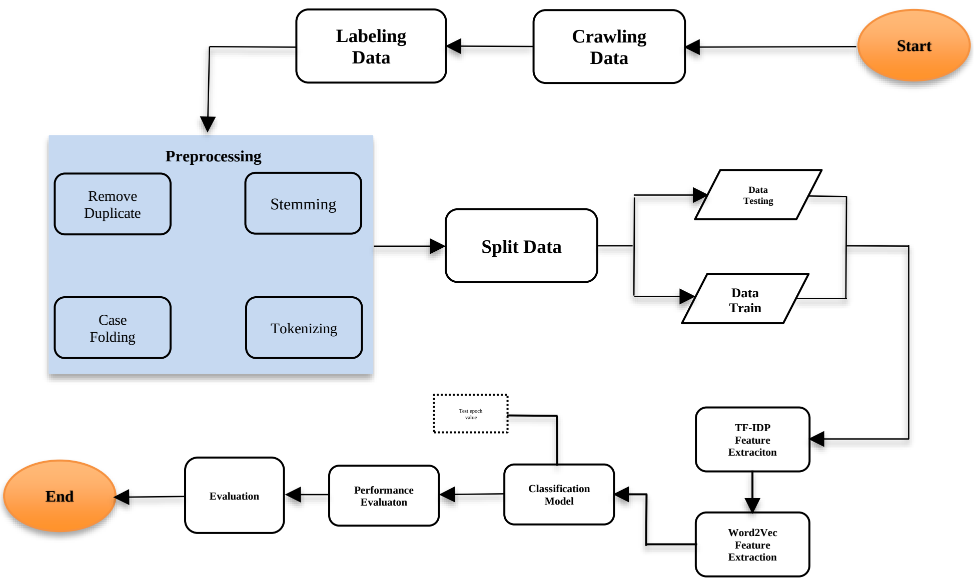

Fig. 2 Flowchar of the System being Built

Data Crawling

Crawling data is the stage of the data collection process. The data used in this research is a review of the Lazada application on Google Playstore in Indonesian. The data crawling process is done using python with the google-play-scrapper library. This library has an API service for scraping data from the Data crawling process is done

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using python with the google-play-scrapper library. This library has an API service for scraping data from Google Playstore. The data to be collected is about 5000 review data.

Data collection using the crawling method using the API provided using the python programming language and also assisted by the google-play-scrapper library. The data obtained from the results of crawling data in the form of files in Comma Seperated Values (CSV) format containing Lazada keywords.

Data Labeling

The data that will be used in this study are the results of the Playstore application users' opinions about Lazada e-commerce that have been collected. Then the data that has been collected will be carried out in the data labeling stage which is divided into two labels, namely positive and negative based on data from playstore application reviews.

The labeling done in this research is positive and negative. From the entire document, it will be identified whether the Lazada application review is positive or negative. A positive sentence is a review that provides good feedback if the user is satisfied with the responsive service and will be labeled '1', while a negative one is when the user receives poor product quality or dissatisfaction with the service received and is labeled '-1'. The dataset obtained is 10.000

Table 1. Example of Labeling Results

Review	Label
Woi ngnt lu kalo iklan jangan maksa napa kontool	-1
Aplikasi gk jelas, saya pesen barang tpi yg di kirim tak sesuai rekomendasi	-1
belanja di LAZADA,memang lebih murah,cepat dan amanah	1
woww bagus sekali aplikasi aini good	1

Table 2. Data Used

Positive	Negative
3,349	2609
Total	5,958

Preprocessing Data

At this stage the data that has been obtained previously will be given sentiment. After the data that has been obtained is given sentiment, after that the data will enter the data preprocessing stage. Preprocessing has several stages in the data such as Remove duplicates, Case Folding, Tokenizing, Stemming (Dwiki et al., 2021).

Preprocessing is the first step before classification. Preprocessing aims to clean and change unnecessary data so that it can make it easier to process data that will be used for the classification process.

The following is a flowchart of the preprocessing stages applied:

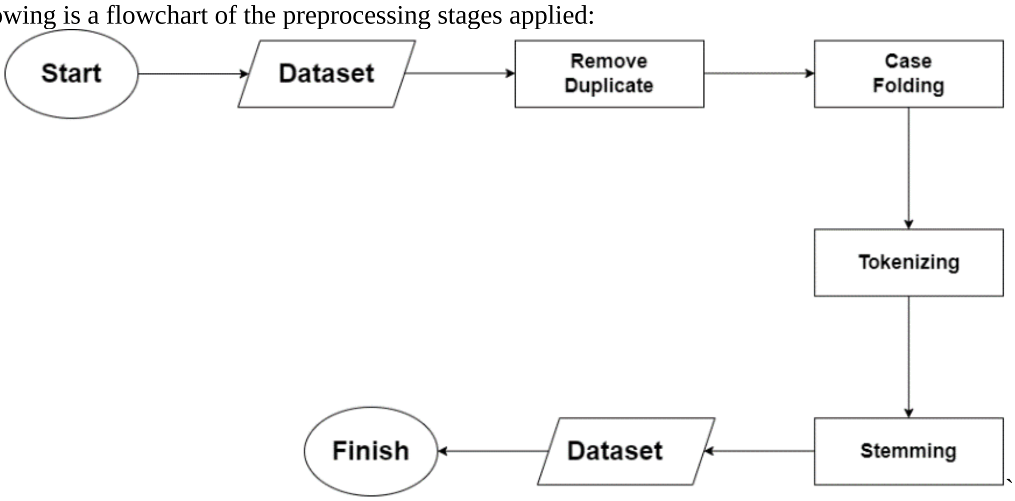

Fig. 3 Flowchar Diagram Preprocessing

*name of corresponding author

Tabel 3. Pre-processing data

Pre-processing	Review	Result
Remove Duplicate	Kok gak bisa mulu sii udh 2x coba ttep aja gak bisa di instal..moho selesaikan masalah ini ya untuk yang bkin ini	Kok gak bisa mulu sii udh x coba ttep aja gak bisa di instal moho selesaikan masalah ini ya untuk yang bkin ini
Case Folding	Kok gak bisa mulu sii udh x coba ttep aja gak bisa di instal moho selesaikan masalah ini ya untuk yang bkin ini	kok gak bisa mulu sii udh x coba ttep aja gak bisa di instal moho selesaikan masalah ini ya untuk yang bkin ini
Tokenization	kok gak bisa mulu sii udh x coba ttep aja gak bisa di instal moho selesaikan masalah ini ya untuk yang bkin ini	['kok', 'gak', 'bisa', 'mulu', 'sii', 'udh', 'x', 'coba', 'ttep', 'aja', 'gak', 'bisa', 'di', 'instal', 'moho', 'selesaikan', 'masalah', 'ini', 'ya', 'untuk', 'yang', 'bkin', 'ini']
Stemming	['kok', 'gak', 'bisa', 'mulu', 'sii', 'udh', 'x', 'coba', 'ttep', 'aja', 'gak', 'bisa', 'di', 'instal', 'moho', 'selesaikan', 'masalah', 'ini', 'ya', 'untuk', 'yang', 'bkin', 'ini']	['kok', 'gak', 'bisa', 'mulu', 'sii', 'udh', 'x', 'coba', 'ttep', 'aja', 'gak', 'bisa', 'di', 'instal', 'moho', 'selesai', 'masalah', 'ini', 'ya', 'untuk', 'yang', 'bkin', 'ini']

TF-IDF Feature Extraction

The Term Frequency-Inverse Document Frequency (TF-IDF) is a method that is useful in assessing the relative weight of each frequently occurring word. The word weighting stage becomes a very crucial step after going through the preprocessing process. The purpose of word weighting is to transform initially unstructured data into more structured data. TF-IDF method is the most typical text similarity measure algorithm, and it represents the text as a vector composed of n weighted words terms that appear in the text by following empiric observation (Lan, 2022).The main purpose of the TF-IDF approach is to assess how significant a word (term) is in a document, taking into account the context of the entire larger document set. Feature extraction applies word2vec and Term Frequency - Inverse Document Frequency (TD-IDF) techniques. TD-IDF is a word2vec-based feature extraction process that applies values to features based on the frequency of occurrence of these features in the data (Ferdiana et al., 2019).

The feature expansion used in this research is TF-IDF. The weighting process in TF-IDF consists of calculating the Term Frequency (TF) value, which is the frequency of occurrence of words transformed in the form of log tf and Inverse Document Frequency (IDF), which is the calculation of a term (sentence) in all documents. The results of the process are in the form of a matrix consisting of rows and columns where data is a row and features are a column. For calculations with the TF-IDF method can be seen in the following equation:

$$TF\ (tk, df) = f(tk, dj) \quad (1)$$

$$IDF(tk) = \log\log \frac{N}{\mathrm{df(t)}} \quad (2)$$

$$w(t, d) = t(f, d) * idf(t) \quad (3)$$

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Description:
In equation (1), (tk,dj) is the number of occurrences of term (k) in document (j).
In equation (2), IDFi is the value of inverse document frequency, while N is the total number of documents, and dfi is the number of documents containing word i.
In equation (3), w(t,d) is the weight of term (t) on document (d), while t(f,d) is the number of occurrences of term (t) in document (d), and idf(t) is the value of inverse document frequency.

Word2Vec Feature Extraction

Word2Vec transforms each unique word as a vector. The advantage of Word2Vec is that it can represent the contextual similarity of two words in the resulting vector (Zhu, 2017). Word2Vec is a word vector representation algorithm that achieves the best performance in NLP (Natural Language Processing) by clustering similar words into the same vector (Intan Af et al., 2021). Word2Vec computes word representations into vectors using a neural network. The resulting word vectors are space-dimensional vectors that capture the semantic meaning of the word (Nawangsari, 2019). Word2Vec is typically beneficial for enhancing classification accuracy due to the fact that in Word2Vec, words with similar meanings possess comparable vectors, leading to improved performance in classification tasks.

Classification Model

After feature weighting, the next step is the classification process. The method used in this research is the RNN classification method. RNN was chosen because this model is considered efficient for sentiment analysis. RNN also has an internal memory capable of obtaining information about long sequences. This method processes data sequentially.

Performance Evaluation

The evaluation stage is carried out to be able to determine the level of performance of the model that has been made. If the performance value owned by the system has a large value, the classification that has been carried out is effective. Performance calculations in this study use k-cross validation where this method is commonly used in machine learning to objectively evaluate model performance based on accuracy, precision, recall, F1 score. true (True Positive) compared to the overall positive actual data. F1-Score is a weighted average comparison of precision and recall. The four values can be calculated using the following formula:

Some performance measures include, namely accuracy, the value of the closeness of the prediction results to the actual results can be calculated by equation 1. Precision is obtained based on the value of the ratio of positive true predictions to positive-valued data in the entire data, the calculation can use equation 2. Recall is obtained based on the results of the ratio of positive true to data that is positive true value in the entire data, the calculation uses equation 3. F1 score is the precision and recall values that have been combined using equation 4 (Alghifari et al., 2022). The evaluation of the model is carried out with the assessment parameters of the confusion matrix. The confusion matrix is a method used to assess the performance of prediction results in a classification system. Four parameters are employed in this method: true positive (TP), false negative (FN), true negative (TN), and false positive (FP).

Tabel 4. Confusion Matrix

		True Class	
		Positive	Negative
Predicted Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FN)	True Negative (TN)

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \qquad (4)$$

$$Precision = \frac{TP}{TP + FP} \qquad (5)$$

$$Recall = \frac{TP}{TP + FN} \qquad (6)$$

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$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (7)$$

RESULT

Evaluation

The evaluation stage is carried out to be able to determine the level of performance of the model that has been made. If the performance value owned by the system has a large value, the classification that has been carried out is effective. The calculation of performance in this study uses k-cross validation where this method is commonly used in machine learning to objectively evaluate model performance based on accuracy, precision, recall, F1 score.

In this study, a test scenario was carried out using the RNN-LSTM classification model. Some of the parameters used in this model are epoch, dropout and batch size. In testing, several experiments were carried out with different epoch and dropout variant values. In the first test, the epoch value used was 5 and the dropout value was 0.2. Until five experiments were carried out epoch 5,10,15,20,25 and dropout values of 0.2, 0.4, 0.6, 0.8, 0.10 with a batch size value of 32.

Testing Results

In the test results with experiments carried out to get the best accuracy value from several experiments with different epoch and dropout variation values. By using TF-IDF feature extraction, this research has the goal of analyzing sentiment using deep learning methods. K-Fold is used in each test to evaluate the accuracy of the classifier in predicting the correct class, whether positive or negative.

Table 5. Accuracy Results with 5 x 5 Matrix

Dropout \ Epoch	5	10	15	20	25
0.2	85.34%	83.72%	82.49%	82.10%	81.59%
0.4	85.34%	84.06%	82.77%	82.38%	81.82%
0.6	84.57%	84.78%	83.61%	82.32%	81.87%
0.8	**86.18%**	85.40%	84.34%	83.78%	83.38%
0.10	85.01%	83,16%	82.27%	.82.15%	81.48%

Testing results with different epoch and dropout values, the accuracy results are obtained with an epoch value of 5 and a dropout of 0.8 using a batch size value of 32.

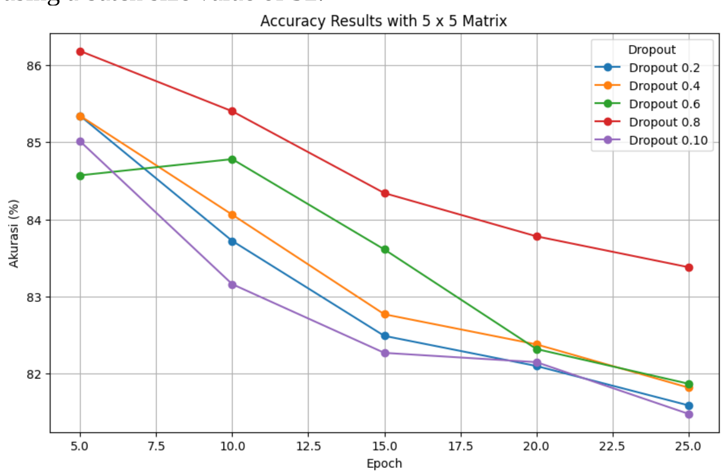

Fig. 4 Accuracy Graph Results with 5 x 5 Matrix

There is a correlation between the dropout rate and the number of epochs in this study that uses the Recurrent Neural Network (RNN) method. In the data used in this study, when the epoch value and dropout value used are

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high, it affects the accuracy value so that it does not get the best accuracy value. Determining a parameter used can produce good results.

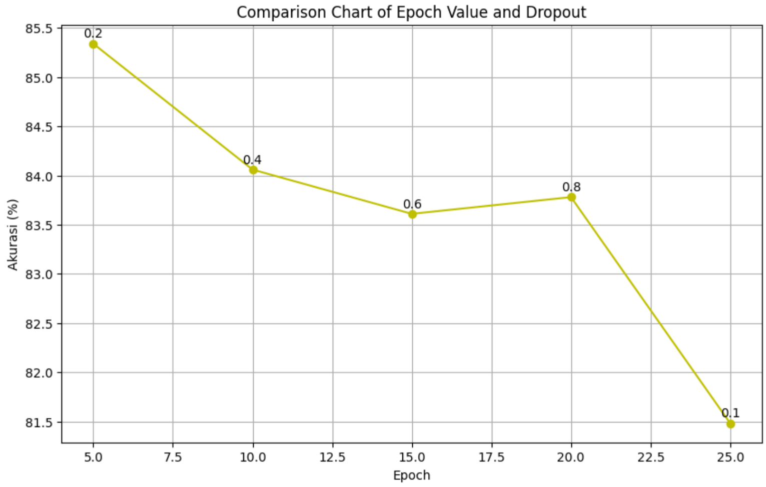

Fig. 5 Comparison Chart of Epoch Value and Dropout

Based on these results, it can be seen that the smaller the epoch and dropout values, the better the accuracy. the accuracy results obtained. And it can be concluded that the epoch value greatly affects the value of accuracy results. By applying TF- IDF weighting which is common in text management and more structured information, and the weighting results depend on the type of data used.

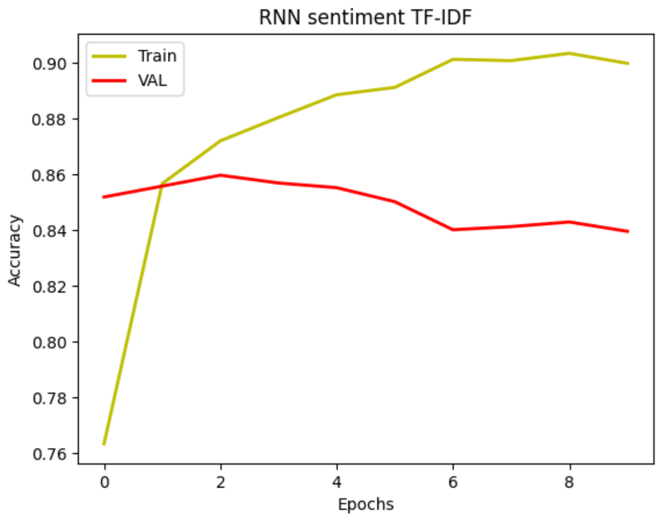

Fig 6. Accuracy graph of the Epoch value in TF IDF scenario

DISCUSSIONS

This research is geared towards analysing and understanding the sentiment of satisfaction or service on the Lazada app by using the RNN-LSTM algorithm. Additionally, product marketing can be done effectively through word-of-mouth methods, an approach that is difficult to achieve through traditional advertising. Users can also raise about contests held by sellers on the Lazada platform. Diverse text datasets and complex word relationships also influence these fluctuations. The Lazada app review dataset included words that were not in the word2vec model pre-trained with the Wikipedia corpus, leading to inconsistencies.

Based on several experiments that have been conducted, the Recurrent Neural Network (RNN) model with Long Short-Term Memory (LSTM) shows good performance when applying the TF-IDF feature weighting method. In the experiments conducted, five epoch numbers were taken, namely 5,10,15,20 and 25 with dropout values of 0.2, 0.4, 0.6, 0.8 and 0.10. It was found that the epoch value of 5 and the dropout value of 0.8 had better results compared to several other epoch values and dropout values. The accuracy obtained is 86.18%, Precision 85.96%, Recall 85.75% and F1-Score 85.84%.

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CONCLUSION

This research compares the performance of epoch and dropout with varying values. The dataset used is the result of the playstore application regarding public opinion on the lazada application that has been collected. The dataset totalled 5,958, with 2,609 negative labels and 3,349 positive labels, The experimental results show that high epoch and dropout values can make performance less optimal. However, the use of parameters is important for accurate analysis. The rapid use of the internet facilitates an activity, such as doing online shopping can help daily activities and can shorten time. However, online shopping has great risks, and cause reviews are things that can be seen to avoid a risk when buying goods on Lazada. Sentiment analysis is important to understand product development and offer an efficient approach. Further research on large data sets can improve the analysis. The use of the TF-IDF method plays an important role to avoid over-botaging words that appear frequently in documents, thus improving the accuracy of the system in determining the topics discussed in an opinion.

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