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Sentiment Analysis of Student Satisfaction on Telkom University Language Center (LaC) Services on Instagram Using the RNN Method

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Abstract−Social media has become a medium for communication between individuals and aspects of the business, including decision-making processes, brand promotion, brand marketing, and personal branding. One of them is Instagram. Using the comments feature on Instagram, users can communicate and give opinions on an upload on an Instagram account. Sentiment analysis can be done to analyze comments on the LaC (language center) Instagram account to measure student satisfaction sentiment towards Telkom university's LaC (language center) services. This study aims to analyze the sentiment or opinion of student satisfaction with the Telkom University Language Center (LaC) service on Instagram. The author also performs a classification based on positive sentiment, negative, and neutral categories using the Recurrent Neural Network (RNN) method and the Confusion Matrix measurement. From the test results on the model built to get an accuracy value of 79%.

Keywords: Sentiment Analysis; Telkom University; Instagram; Recurrent Neural Network; Confusion Matrix

1. INTRODUCTION

Social media has become a medium for communication between individuals and several aspects of the business field, including decision-making processes, brand promotion, brand marketing, and personal branding [1]. Many companies and organizations use social media to reach the masses. One of them is Instagram. This social media platform was founded in 2010. Until now, Instagram is the sixth most visited website. Instagram has the fourth most users of all mobile applications, and more than one billion people use the Instagram application every month [2].

Sentiment analysis is a field of study that analyzes people's opinions, sentiments, evaluations, assessments of attitudes, and emotions towards entities, such as products, services, organizations, individuals, events, topics, and other attributes [3]. A significant result in sentiment analysis is identifying the emotions expressed in the text, where the expression's result shows a positive or negative opinion based on the topic in question. The problem with sentiment analysis is the amount of data that needs to be tested for manual analysis. Of course, it takes a lot of time and effort, especially if the opinion is in the form of comments. Manual analysis requires analysts to focus on every sentence they read before making a sentiment decision. Therefore it must be done computerized to reduce the time needed to analyze and determine positive or negative opinions.

A Recurrent Neural Network (RNN) is a type of artificial neural network architecture where the process is called in a loop to process input, usually sequential data. RNN is included in the category of deep learning because the data is processed in many layers. RNN has grown rapidly and revolutionized fields such as natural language processing (NLP), speech recognition, music synthesis, financial data processing, DNA sequence analysis, image, video captioning, word prediction, word translation, image processing, speech recognition, and so on [4].

Another method compared to this research is bidirectional LSTM. Bidirectional LSTM is one of the commonly used LSTM variants. Two types of inputs are entered into the bidirectional LSTM, forward input, and backward input. The outputs of these layers are generally combined into one. The model can learn past and future information for each input sequence with this layer [5].

Several studies related to sentiment analysis were carried out. In this study [6], a method was developed for classifying sentiment analysis and identifying the sentiments of each opinion word contained in the response and hashtag data. The results are that posting photo or picture on Instagram make a positive comment from visitor and the impact is increasing visitor to Rinjani Mountain. In this study [7], sentiment analysis was carried out on the movie review. The data used is the result of a film review where the average number of texts in the review is 233 words. The method used is LSTM. The results of this study are the results of accuracy reaching 88.17%. In this study [8], sentiment analysis was carried out on one of the news portals in Indonesia. The method used is the Long Short-Term Memory (LSTM) method. The result states that the LSTM method can analyze the news context well on the news web portal.

Based on several related studies, this study uses the RNN method with the LSTM model to analyze student satisfaction with the Telkom University Language Center (LaC) Service. The data used in one of the differentiators from several related studies have been described. These two things are the difference between this research and previous research.

The author takes the object of research on the Instagram Language Center (LaC) Telkom University account. Since 2016, the Telkom University language center service has started using Instagram to interact with

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its followers, with the number of followers increasing daily. In classifying sentiment analysis, the author uses the Recurrent Neural Network (RNN) algorithm to determine and measure responses in implementing student satisfaction with Telkom University language center and also as an accuracy comparison, the author uses the LSTM bidirectional model. services. The dataset used in this paper was obtained through the data crawling of Telkom University's Instagram Language Center (LaC).

2. RESEARCH METHODOLOGY

The stages carried out in this study are shown in Figure 1. The first stage is collecting data from Instagram comments. The second stage is the existing datasets will be labeled manually, the third stage is preprocessing, the fourth stage is the modeling process using LSTM, the sixth stage is the RNN classification process, and the sixth stage.

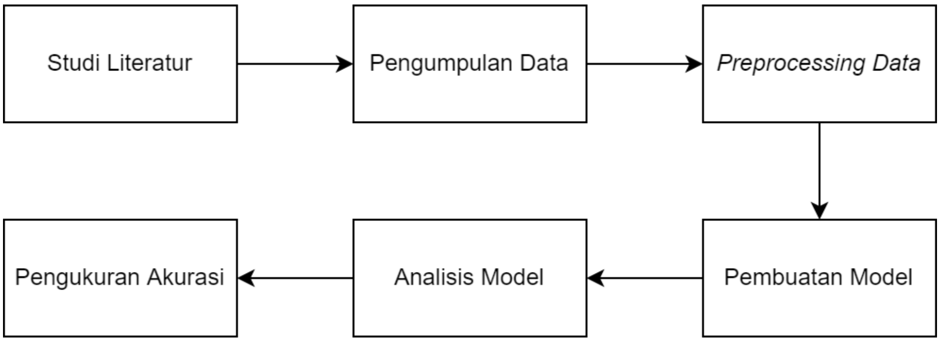

Figure 1. Research Stages

2.1 Literature Study

2.1.1 Related Research

Alpna Patel and Arvind Kumar Tiwari(2019), in a journal entitled "Sentiment Analysis by using Recurrent Neural Network," this study provide a detailed description of the selection of different methods and sentiment classification techniques and deep learning for sentiment analysis. This paper concludes with various deep learning models for sentiment analysis. The Recurrent Neural Network model yields an accuracy of 87.42% on the film review dataset [9]. Another study, "Opinion Mining on US Airline Twitter Data Using Machine Learning Techniques." Sentiment analysis was carried out using various methods, including Lexicon, Machine Learning, Hybrid-Based models, and Deep Learning. This study shows that the SVM method outperforms other classification methods with an accuracy of 83.31% [10]. Furthermore, finally, in the research "Sentiment Analysis in the Light of LSTM Recurrent Neural Networks" in this study, researchers conducted various types of LSTM architecture for sentiment analysis of film reviews. The results indicate that the LSTM RNN is more effective than the deep neural network [11].

2.1.2 Student Satisfaction with Institutional Services

Student Satisfaction with Institutional Services Customer satisfaction, in this case, students, is a measure of how well the product and service meet or exceed the customer's expectations. Service quality compares the expected service with the service it receives [12].

Student satisfaction is influenced by many factors, including responsiveness, the provision of service assistance when students need a fast response, and stability. In this case, the service operates according to the specified value. Content quality is the quality of any content related to services and following student needs. Staff attitudes are crucial factors in increasing student satisfaction. For example, courtesy shows respect and is flexible to reply and explaining student comments on Instagram accounts Language center [13].

2.1.3 Sentiment Analysis

Sentiment analysis analyzes people's opinions, feelings, ratings, attitudes, and feelings towards entities such as products, services, organizations, and other attributes. Opinions mainly he can be divided into three types comparative opinions comparing multiple companies furthermore, suggestive remarks suggesting one or more entities. Regular Opinions are used to identify positive or negative opinions about a product. A comparative opinion, on the other hand, helps explain the relationship between one or more entities, which is incredibly competitive information. [3].

Sentiment analysis or opinion mining has been introduced as an effective way to find knowledge based on commented expressions, especially in the web context. Sentiment analysis or opinion mining also extracts opinions, user sentiments, and demands from subjective texts in specific domains and distinguishes the patterns [14].

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2.1.4 Recurrent Neural Network (RNN)

A Recurrent Neural Network (RNN) is part of a neural network to process data continuously. To store information, RNN loops in the architecture and stores past information.
RNN has grown rapidly and revolutionized fields such as natural language processing (NLP), speech recognition, music synthesis, financial data processing, DNA series analysis, image, video captioning, word prediction, word translation, image processing, speech recognition, and so on [4].

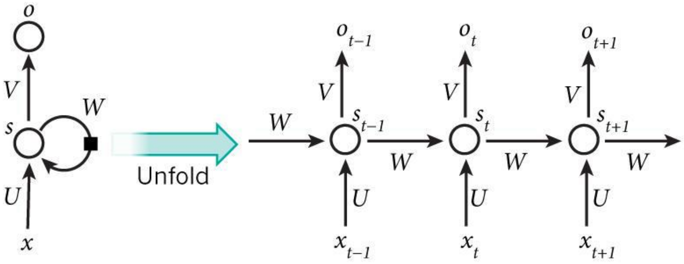

Figure 2. RNN architecture

2.1.5 Long Short Term Memory fundamental

Recurrent neural networks (RNNs) are well suited for performing natural language processing (NLP) tasks. MajoritRNN users use Long Short Term Memory (LSTM) because LSTM is considered very good at executing long-term dependencies compared to other RNN types. SeppHochreiter and Jürgen Schmidhuber first published his LSTM in 1997. However, LSTM has become one of NLP's most popular and widely used models [15].

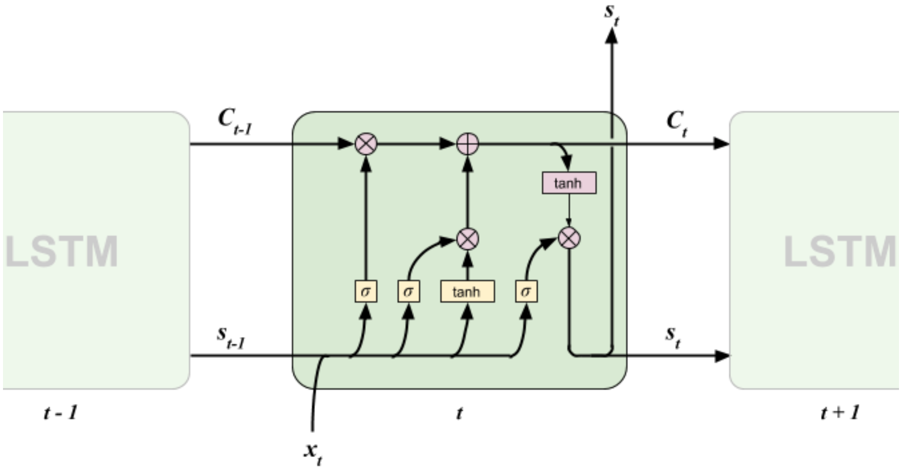

Figure 3. LSTM Network

2.2 Data Collection

This research requires data from comments on Instagram. To obtain data in the form of Instagram comments, the author uses a web scrapping method on Instagram comments then the data is converted into .csv format.

The case study in this study uses data from scrapping comments on the Telkom University Instagram Language Center (LaC). The data obtained from the results of the Instagram comment scrapping process is divided into two parts. The first part of the dataset is used as a train dataset or training data for making sentiment analysis models. The second part is a test dataset or test data. This second part of the dataset will be used in sentiment analysis, classification, and evaluation.

2.3 Preprocessing

As a result of scrapping Instagram comments, the first part of the dataset is still an unlabeled dataset, i.e., datasets that do not yet have positive and negative labels. The labeling process for this sample dataset is done manually, resulting in a dataset with positive and negative labels. In the following process, the data will be converted into a structure for the analysis process. The preprocessing stages carried out in this study were case folding, data cleaning, stopwords removal, and tokenization.

2.4 Modeling

The fourth stage of this research is model making. At this stage, the model of the LSTM will be used. The model is made to carry out sentiment analysis. The sentiment analysis results are in the form of a model classification. They are divided into two, i.e., positive and negative.

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2.5 Model Analysis

The model that has been made will be analyzed to measure the level of accuracy of model making. Accuracy is the benchmark for the results of the analysis. The model is also run with a configuration of 8 epochs, n learning rates, and n dropouts to find the highest accuracy value from the model created.

2.6 Measurement Accuracy

Measurement of accuracy is used to evaluate the performance of the model that has been built. Measurement of accuracy uses a confusion matrix to see the test results in the form of 4 parameters, i.e., accuracy, precision, recall, and F1-score.

3. RESULTS AND DISCUSSION

This section describes the results of the research conducted.

3.1 Data Collection Results

When collecting data, the author uses the Instagram web scrapping technique. From the results of web scrapping, 1180 data were collected, then the dataset collection will be stored in .csv format.

Dataset will be divided into two parts, train dataset and test datasets. Sharing process dataset necessary for the system to perform training so the system can classify student satisfaction with the services language center (LaC). The following table 1 is a division dataset that will be used.

Table 1. Data Colletion Result

Dataset	Train Dataset	Test Dataset
1180 Instagram Comment	90% From Dataset	10% From Dataset

3.2 *Preprocessing*

The dataset will be labeled in preprocessing and proceed to other stages such as case folding, data cleaning, stopwords removal, and tokenization. Preprocessing is needed to remove components that are not needed for analysis, such as punctuation, mentions, and URLs. Stopwords are used to remove words that often appear in a text. Words that often appear in the text are not helpful for retrieving information and must be removed to avoid interfering with the analysis process. Tokenizing serves to convert the sentence in the dataset into an integer.

3.2.1 Labeling

The raw data will be cleaned at the labeling stage by deleting data columns that are not needed for the analysis process. Then the data will be labeled manually, i.e., 1 (positive) or 0 (negative). Examples of data used in this study can be seen in table 2. Table 3 is data that has been manually labeled.

Table 2. Raw Data Instagram Comments

PK	User_id	Text
17888356388606677	9426263406	Selamat kepada para pemenang!
17931300064706515	32000198064	Link tidak bisa di akses min
17924243285018148	2270728854	Alhamdulillah, terima kasih kakak-kakak penyelenggara
17998184329148161	3221358011	Ga bisa diklik link youtube-nya...
17977968937338707	1578664091	@lac.telkomuniv baik, terimakasih info nya min

Table 3. Data With Label

Text	Label
Selamat kepada para pemenang!	1
Link tidak bisa di akses min	0
Alhamdulillah, terima kasih kakak-kakak penyelenggara	1
Ga bisa diklik link youtube-nya...	0
@lac.telkomuniv baik, terimakasih info nya min	1

3.2.2 Case Folding

Case folding is helpful for uniform letterforms so that the sentences in the data only become lowercase. The difference in letters can interfere with the following process. Therefore, case folding is needed to change the text in Instagram comments to lowercase [16]. Table 4 is an implementation of case folding.

Table 4. Case Folding Results

Text	Case Folding

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Text	Case Folding
Selamat kepada para pemenang!	selamat kepada para pemenang!
Link tidak bisa di akses min	link tidak bisa di akses min
Alhamdulillah, terima kasih kakak-kakak penyelenggara	alhamdulillah, terimakasih kakak-kakak penyelenggara
Ga bisa diklik link youtube-nya...	ga bisa diklik link youtube-nya...
@lac.telkomuniv baik, terimakasih info nya min	@lac.telkomuniv baik, terimakasih info nya min

3.2.3 Data Cleaning

Data cleaning eliminates all punctuation so as not to interfere with the training process [17]. The results of data cleaning can be seen in table 5.

Table 5. Data Cleaning Results

Text	Data Cleaning
Selamat kepada para pemenang!	selamat kepada para pemenang
Link tidak bisa di akses min	link tidak bisa di akses min
Alhamdulillah, terimakasih kakak-kakak enyelenggara	alhamdulillah terimakasih kakak kakak penyelenggara
Ga bisa diklik link youtube-nya...	ga bisa diklik link youtubenya
@lac.telkomuniv baik, terimakasih info nya min	lactelkomuniv baik terimakasih info nya min

3.2.4 Stopwords Removal

Stopwords r**e**moval aims to remove words that often appear in the data and have no significance in the data [18]. An example of its implementation can be seen in table 6.

Table 6. Stopwords Removal Results

Text	Stopwords Removal
Selamat kepada para pemenang!	selamat para pemenang
Link tidak bisa di akses min	link tidak bisa di akses
Alhamdulillah, terimakasih kakak-kakak penyelenggara	alhamdulillah terimakasih kakak penyelenggara
Ga bisa diklik link youtube-nya...	ga bisa diklik link youtube
@lac.telkomuniv baik, terimakasih info nya min	lactelkomuniv baik terimakasih info

3.2.5 Tokenization

Tokenization aims to cut words to separate words from other words in a sentence. Then the word is given an integer that matches the word in the data [19]. The results of its implementation can be seen in table 7.

Table 7. Tokenization Results

Teknik	*Tokenization*
Can't click on the youtube link...	['can't' 'click' 'link' 'youtube'] [24, 5, 978, 43, 451]

3.3 Model Making Results

At this stage, the model is made for sentiment analysis of student satisfaction with language center (LaC) services. The model used is the LSTM model. This model serves to analyze the text of the existing dataset. Figure 3 is a model summary of the model that has been made. Below is the algorithm to create a model using the LSTM model.

Modeling Algorithm

```
model = Sequential()
model.add(Embedding(1000, 256, input_length=X.shape[1]))
model.add(Dropout(0.4))
model.add(LSTM(256, return_sequences=True, dropout=0.4, recurrent_dropout=0.2))
model.add(LSTM(256, dropout=0.4, recurrent_dropout=0.2))
model.add(layers.Dense(2, kernel_initializer='uniform'))
model.add(layers.Activation('softmax'))
hard.optimizers.Adam(learning_rate=0.001)
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()
```

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```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 77, 256)           256000

 dropout (Dropout)           (None, 77, 256)           0

 lstm (LSTM)                 (None, 77, 256)           525312

 lstm_1 (LSTM)               (None, 256)               525312

 dense (Dense)               (None, 2)                 514

 activation (Activation)     (None, 2)                 0

=================================================================
Total params: 1,307,138
Trainable params: 1,307,138
Non-trainable params: 0
_________________________________________________________________
```

Figure 4. Model Summary LSTM

The author conducted 25 experiments for LSTM modeling. Each experiment tests the model's accuracy by adjusting several parameters, such as learning rate and dropout. The experiment was carried out by following the main steps: making the LSTM model, conducting training on the model, and finding the level of accuracy.

3.4 Model Analysis

At this stage, the performance analysis of the LSTM model that has been created will be carried out. The model analysis process is carried out by calculating the accuracy value with experiments conducted by the author. The iteration will be completed when the model has undergone all experiments. Figure 4 is the result of the analysis using experiments and models that have been made.

```
Epoch 1/8
34/34 [==============================] - 50s 1s/step - loss: 0.6894 - accuracy: 0.5537 - val_loss: 0.6823 - val_accuracy: 0.5847
Epoch 2/8
34/34 [==============================] - 38s 1s/step - loss: 0.6404 - accuracy: 0.6008 - val_loss: 0.6216 - val_accuracy: 0.6441
Epoch 3/8
34/34 [==============================] - 41s 1s/step - loss: 0.5070 - accuracy: 0.7401 - val_loss: 0.5857 - val_accuracy: 0.7034
Epoch 4/8
34/34 [==============================] - 38s 1s/step - loss: 0.3847 - accuracy: 0.8126 - val_loss: 0.6276 - val_accuracy: 0.6949
Epoch 5/8
34/34 [==============================] - 38s 1s/step - loss: 0.2936 - accuracy: 0.8653 - val_loss: 0.7277 - val_accuracy: 0.7034
Epoch 6/8
34/34 [==============================] - 41s 1s/step - loss: 0.2586 - accuracy: 0.8832 - val_loss: 0.7770 - val_accuracy: 0.6864
Epoch 7/8
34/34 [==============================] - 38s 1s/step - loss: 0.2118 - accuracy: 0.8983 - val_loss: 0.8922 - val_accuracy: 0.7458
Epoch 8/8
34/34 [==============================] - 39s 1s/step - loss: 0.1716 - accuracy: 0.9237 - val_loss: 1.0410 - val_accuracy: 0.7288
```

Figure 5. Model Accuracy Calculation Results

3.5 Measurement Accuracy

In testing this system, the author uses a hyperparameter configuration with four variations of learning rates of 0.001, 0.002, 0.003, 0.005, and 0.007. The batch size used is 32, and 5 types of dropouts are 0.3, 0.4, 0.5, 0.6, and 0.8 on the accuracy parameter, precision, recall, and f1-score with the LSTM model for the main study. The authors use the LSTM bidirectional model to compare the accuracy results. Tests were carried out with the same configuration for both models. Figure 5 shows the accuracy comparison between the LSTM and bidirectional LSTM models.

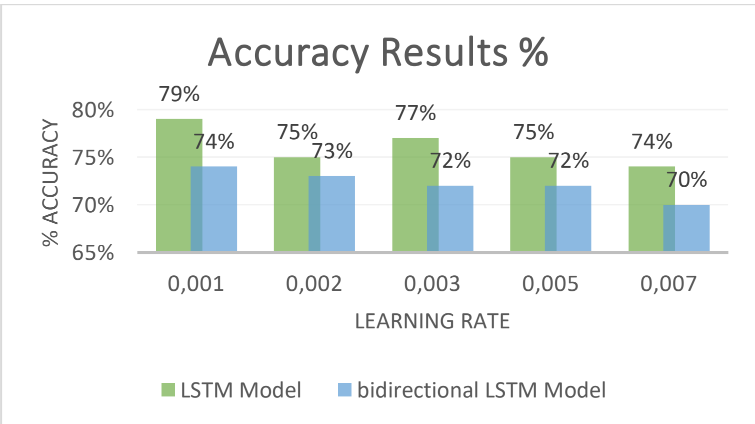

Figure 6. Accuracy LSTM model vs Bidirectional LSTM Model

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From the results of the accuracy test chart between the 'LSTM model' and the "bidirectional LSTM model". The accuracy results for the 'LSTM model' in the 0.001 configurations reached 79%, then the 'bidirectional LSTM model' reached 74%, in the 0.002 configurations it reached 75% for the 'LSTM model' then the 'bidirectional LSTM model' only reached 73%, in the 0.003 configurations the "LSTM model" reached 77%. In contrast, the bidirectional LSTM model reached 72%, in the 0.005 configurations, the "LSTM model" reached 75% and the "bidirectional LSTM model" only reached 72 %. The last configuration with a learning rate of 0.007 became the lowest for both models, with 74% accuracy for the LSTM model and 70% for the bidirectional LSTM model. From these results, it can be determined that the best accuracy of the two models is the "LSTM model." Based on the researchers' comparison results, the highest score was 79%, with a learning rate configuration of 0.001 and a dropout of 0.4. Furthermore, Figure 6 compares the precision between the LSTM model and the bidirectional LSTM model.

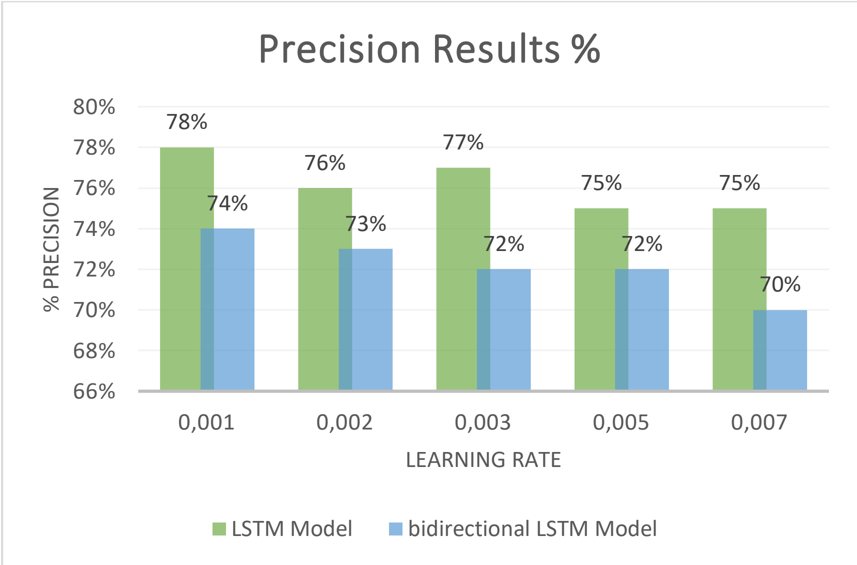

Figure 7. Precision LSTM Model vs Bidirectional LSTM Model

The best precision value obtained is 78% at a learning rate of 0.001 with the "LSTM model." In comparison, the best precision value in the "bidirectional LSTM model" only gets a value of 74% with a learning rate of 0.001. The precision parameter is used to provide information on how accurate the model is in predicting positive or negative sentiment towards the Instagram dataset of Telkom University's LaC (language center) service. Figure 7 compares the recall between the LSTM model and the bidirectional LSTM model.

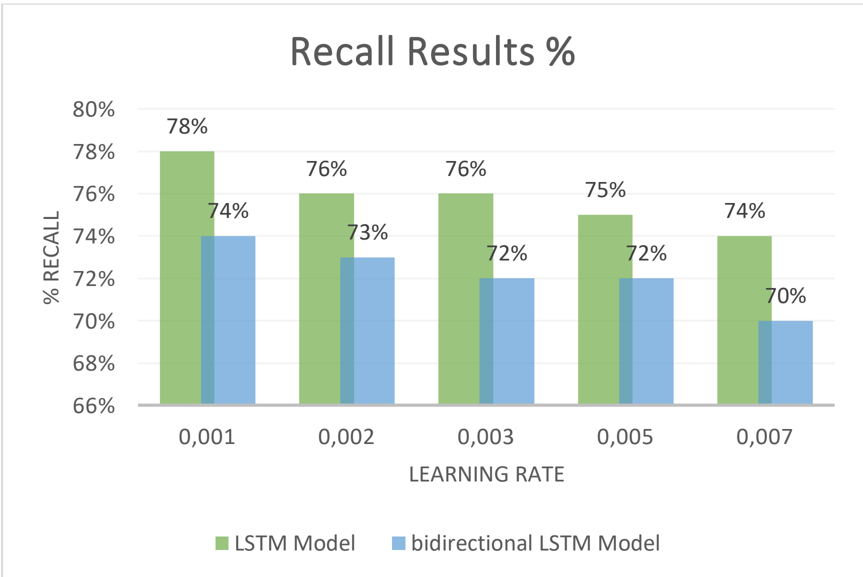

Figure 8. Recall LSTM model vs Bidirectional LSTM model

From the test results on the recall parameter, the average best value obtained is 78% at a learning rate of 0.001 with the LSTM model. Recall describes the model's success in predicting data relevant to Telkom University's LaC (language center) service sentiment.

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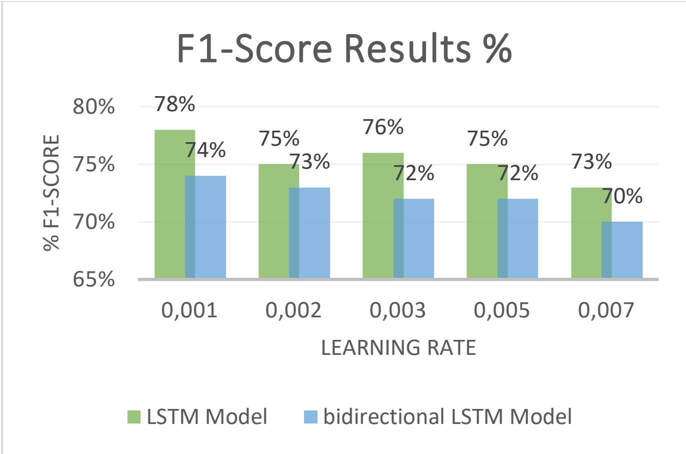

Figure 9. F1-Score LSTM model vs Bidirectional LSTM model

From the test results on the F1-Score parameter in figure 8, the best value obtained is 78% at a learning rate of 0.001 for the LSTM model and 74% for the bidirectional LSTM model. The F1-Score parameter is used to compare the average value of precision and recall, then serves to determine the optimal balance between precision and recall values.

The results of the confusion-matrix test get the highest accuracy value of 79% at the learning rate configuration of 0.001 and dropout of 0.4 for the "LSTM model." Furthermore, for the weighted average on precision and recall parameters, f1-score each gets a value of 79%. The following figure 9 is a classification report and confusion matrix.

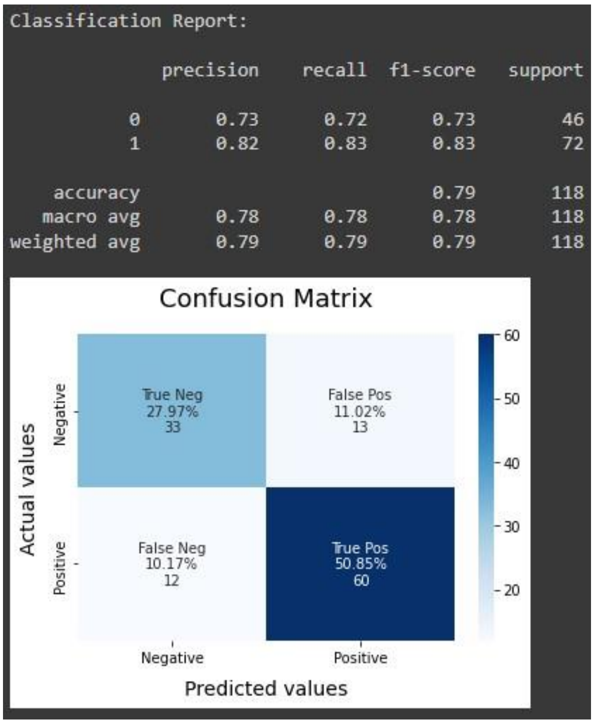

Figure 10. Classification Report with Confusion Matrix

With these results, it can be concluded that a learning rate of 0.001 and a dropout of 0.4 are the best parameters that can be used in this sentiment analysis system.

The support class 0 and support class 1 variables represent the number of test datasets classified as LaC (Language Center) Instagram comments that contain positive and negative elements. In a system with a learning rate of 0.001, the number of support for class 0 and class 1 is 118. This means that the system classifies 46 Instagram comments in class 0 and 72 Instagram comments in class 1. The test dataset is labeled "0" and is predicted to be true negative up to 33 Instagram comments. And false positives in as many as 13 Instagram comments. This means that the test dataset labeled "0" correctly predicted up to 33 comments (including negative Instagram comments) and only 12 incorrectly predicted comments (Negative comments but predicted positive comments). For the test dataset labeled "1", Up to 60 Instagram comments are predicted to be true positives, and 13 comments are predicted to be false.

4. CONCLUSION

Based on the results of tests and analyzes that have been carried out. The sentiment analysis system with the RNN method can be concluded from the results of testing the accuracy parameters. The system gets the highest accuracy of 79% using the LSTM model, and configuration learning rate of 0.001, and a dropout of 0.4 with a value. The epoch value is 8, and the batch value is 32. In comparison, the lowest accuracy obtained by the system is 61%, with a learning rate configuration of 0.005, dropout of 0.8 with an epoch value of 8, and a batch value of 32. The system gets an average value based on testing the precision parameter. The highest average precision is 78% using a learning rate of 0.001, a dropout of 0.4 with an epoch value of 8, and a batch value of 32. In comparison, the average value of the lowest precision obtained by the system is 63% using learning rates of 0.002 and 0.005, dropout 0.3 and 0.8 with epoch value of 8 and a batch value of 32. Based on testing of the recall parameter, the system gets an average value of the highest recall is 78%, using a learning rate of 0.001, dropout is 0.4 with an epoch value of 8 and a batch value of 32. In comparison, the lowest recall average value obtained by the system is 63% using a learning rate of 0.002 and 0.005, dropout of 0.3 and 0.8 with an epoch value of 8, and a batch value of 32. Based on testing for the F1-Score parameter, the system gets the highest average F1-Score value of 78%, using a learning rate of 0.001, a dropout of 0.4 with an epoch value of 8, and a batch value of 32. In comparison, the lowest average F1-Score obtained by the system is 61% using a learning rate of 0.005, a dropout of 0.8 with an epoch value of 8, and a batch value of 32.

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