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| RESEARCH ARTICLE

Sentiment Analysis of Tourism Objects on Trip Advisor Using LSTM Method

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| ABSTRACT
This study developed a sentiment analysis application for comments on tourist sites. It is used to help people who want to know about tourist attractions information to get positive or negative information. The method used to analyze the sentiment was LSTM. The determination of LSTM architecture consists of scraping data, manual labelling, preprocessing (case folding, removing punctuation, removing stopwords, tokenization, and lemmatization), word2index, word embedding, and LSTM layer. In order to achieve optimal accuracy, it is necessary to determine the right embedded method, the total number of layers for the dropout layer, and LSTM. The performance of this study showed that the accuracy and loss from sentiment analysis using the LSTM method were 96.71% and 14.22%.

| KEYWORDS

Sentiment Analysis, Preprocessing, Long Short Term Memory, Word Embedding, Dropout Layer.

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1. Introduction
1.1 Background
Based on 2019 monthly foreign tourist arrivals data, foreign tourist visits to Indonesia in October 2019 totaled 1,354,396 visits, or an increase of 4.86% compared to last year (Kemenpar, 2019). This can bring considerable benefits, one of which is in the economic field because it can attract visitors from within and outside the country to the tourist area.

Based on this description, an area must have the availability of information so that other tourists can know an area or place with high economic potential. One way that can be used to find information in determining whether a tourist place is interesting/worthy to visit is to read the comments of other tourists.

In this research, the tourism platform used is Trip Advisor, which does not only focus on accommodation but also on tourist attractions. Trip Advisor is the world's largest travel site that helps tourists plan their trips. As many as 463 million people have been helped through the Trip Advisor platform. With today's technological advances, people can easily get this information. However, people still need time to read the available reviews before deciding which tourist attractions to visit. One trend that is currently being utilized is Natural Language Processing (NLP) which is a branch of Artificial Intelligence (AI) that focuses on natural language processing. By utilizing one of the areas of NLP, namely document classification, the information in the comments on the website, https://www.tripadvisor.com, can be processed.

Sentiment analysis is a study consisting of Natural Language Processing, linguistic computing, and text analysis to identify text sentiments (Vinodhini and Chadrasekaran, 2016) which can identify opinions about a tourist place conveyed by other tourists in expressing emotions which are usually divided into two classes are positive and negative. Of course, manually analyzing everyone's reviews can be done. However, with Trip Advisor data which has a large amount of real-time data that will continue to grow, a document classification system is needed to make it easier to analyze sentiment.

There is a popular model in NLP, Recurrent Neural Network, where RNN helps us manage sequential information such as sentences in chat. Although RNN theoretically can manage sequential information, RNN is still limited in accessing information if it has a very long sequence. Therefore in this study, we decided to use LSTM, where LSTM can overcome the problems contained in the RNN. Comments on Trip Advisor are generally paragraphs with a long sequence so that LSTM is efficient in recording information dependent on one another. This is supported by several studies reviewed by the author regarding the LSTM method, namely a study by (Dan Li and Jiang Qian, 2018) entitled "Text Sentiment Analysis Based on Long Short-Term Memory", which states that the accuracy results of LSTM have higher accuracy. Compared to RNN.

Based on the needs above, a study was conducted on the classification of comments on Trip Adviser's travel platform, using the Long Short Term Memory (LSTM) method. The study results are useful for people who want to travel to get information about a place more quickly.

2. Research Methods

The research method used in this thesis consists of several stages, namely:

1. *Scraping* Trip Advisor Data

The review data used to represent positive and negative emotions in this thesis uses data from Trip Advisor, which is accessed manually.

2. *Manual Labeling*

The review data that has been collected will be categorized based on sentiment into two parts, namely, positive and negative.

3. *Preprocessing*

In this section, all review data that has been taken will pass through several stages, namely *case folding, remove punctuation, remove stopword*, *tokenization*, and *lemmatization* which will produce clean review data.

4. *Split and Modify Data*

At this stage, the Trip Advisor review data will be divided into two parts, namely *training* and *testing* data, after which the data will be converted into an integer matrix of the same length.

5. LSTM

In this stage, the data will be trained, which will produce a model that can be used to predict whether the sentence is positive or negative.

6. Model Evaluation

At the model evaluation stage, a calculation will be made of how well the system is in classifying the sentiments of the Trip Advisor review data tested on the system.

3. Results and Discussion

In the model training stage, there are several things that must be done to produce an optimal model. This includes choosing the word embedding method, dropout layer, and the number of Long Short Term Memory (LSTM) layers.

At the initial stage, choose the appropriate word embedding method. There are several methods of word embedding, including word2vec and GloVe. The first experiment used word2vec based on IMDB movie data.

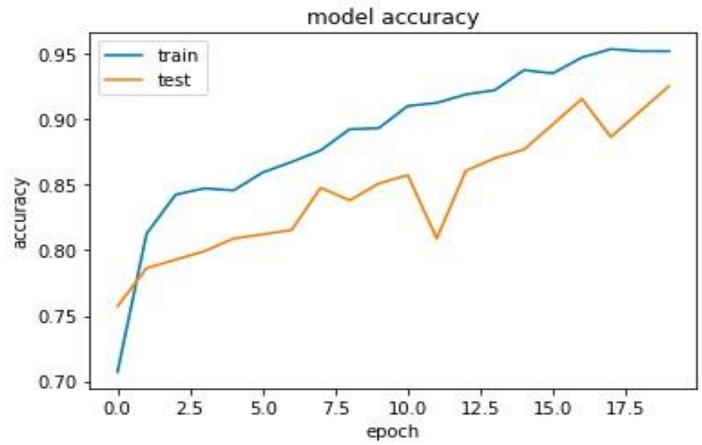


Figure 1 Accuracy Performance Graph By Conducting IMDB Pretrained Training (Word2vec)

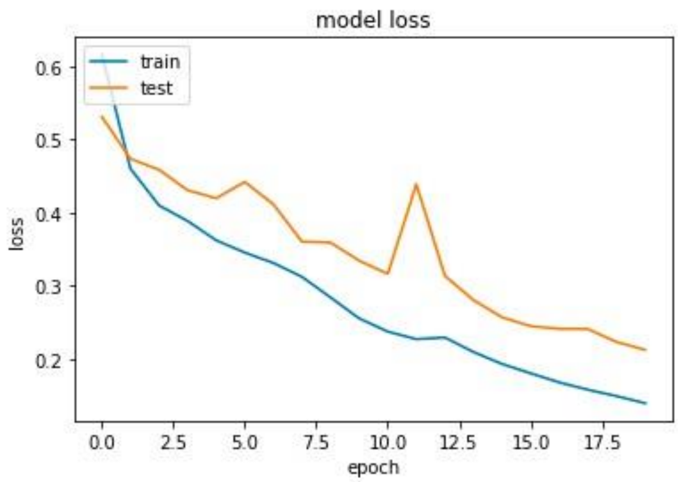


Figure 2 Graph of Loss Performance by Conducting IMDB Pretrained Training (Word2vec)

In model training, using the word2vec method by conducting training on training data produces 92.16% *accuracy and 21.04% loss*. So if you look at the accuracy data, it is good, but it does not represent the appropriate data.

In the second experiment, we tried to use pre-trained word embedding with GloVe, where the dataset used by GloVe embedding is general data. The model's accuracy using GloVe can be seen in Figures 3 and 4 for graphs of *accuracy and loss.*

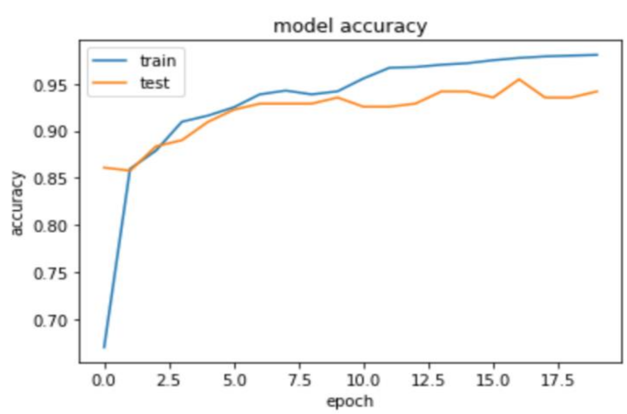


Figure 3 Accuracy Performance Graph Using

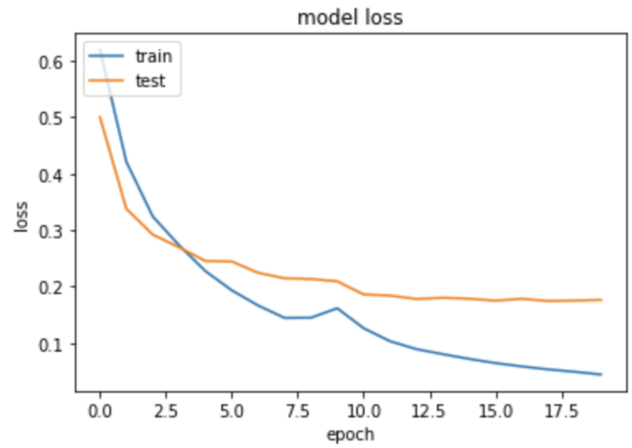


Figure 4 Performance Loss Graph Using Pretrained Word Embedding (GloVe)

In model training using the GloVe method, it produces 96.43% *accuracy* and 17.12% loss. In this research, the accuracy number has produced a good *accuracy*.

Table 1Comparison of Accuracy Using Word2vec and GloVe

	Accuracy	***loss***
Word2Vec	92.16%	21.04%
GloVe	96.43%	17.12%

Based on table 1, word2vec with the IMDB movie dataset has lower accuracy than GloVe because GloVe covers a wider vocabulary than word2vec. In addition, GloVe has better results because it combines two models, namely CBOW and Skip-Gram. Therefore, this study uses *pre-trained word embedding*, namely GloVe.

In using GloVe embedding, there is still *over-fitting*, so a dropout layer is added in the next experiment to prevent *over-fitting* according to the tips given by Chris Albon (2018).

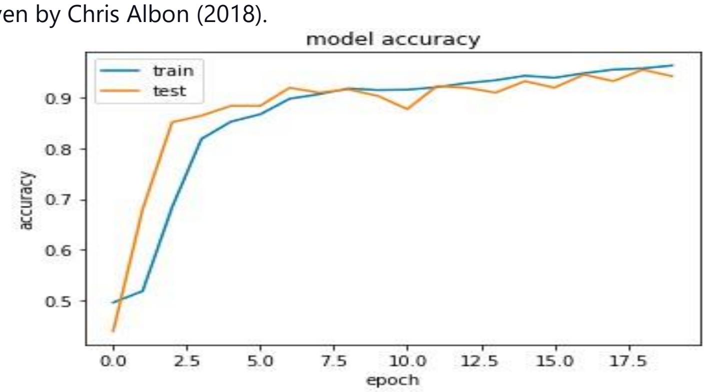
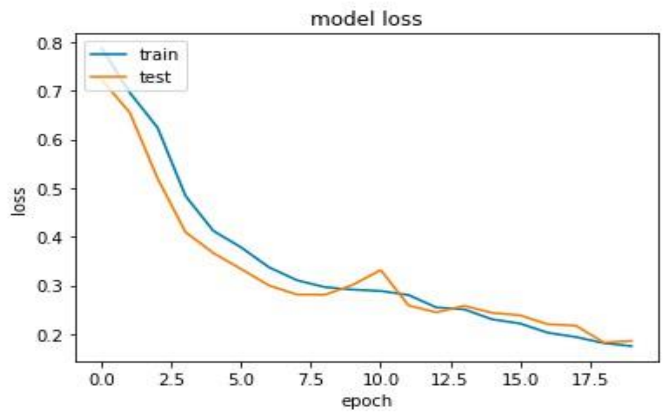


Figure 5 Graph Performa Accuracy with 2 Dropout Layers



Gambar 6 Grafik Performa Loss with 2 Dropout Layer

The graph showing two *dropout layers* in this study proved that it could prevent *over-fitting*. Therefore, the author chose two *dropout layers* to be a reference for the next *improvement*.

It can be seen in Figures 1 and 2 that the accuracy and loss performance graphs using two dropout layers are no longer over-fitting, but improvements will be made in the study to improve accuracy. Therefore, two LSTM layers will be added in this study to increase accuracy and reduce loss.

Table 2 Comparison of LSTM 1 and 2 Layer

	Accuracy	***loss***
1 LSTM Layer with 2 Dropout Layers	94.92%	18.06%
2 LSTM Layer with 2 Dropout Layer	96.71%	14.22%

Based on table 2, the most optimal model in this research is a two-layer LSTM using GloVe embedding and 2 *dropout layers*.

4. Conclusion

Based on the evaluation of sentiment analysis applications for tourist objects, several conclusions can be drawn:

1. Sentiment analysis applications are useful for analyzing tourist attractions that are suitable to visit based on comments on the tourist attractions you are looking for so that the process can be carried out efficiently.
2. The choice of word embedding is very important in improving model training performance to get optimal performance. From the experimental results, GloVe produces better accuracy because GloVe includes a wider vocabulary than word2vec.
3. Model training and validation by adding a Dropout Layer prevented the model from overfitting by producing an accuracy of 94.92% and a loss of 18.06%.

After conducting experiments using 1 LSTM layer and 2 LSTM layers, it is seen that 2 LSTM layers produce better accuracy with 96.71% results and 14.22% loss. Therefore, it can be concluded that in this study, adding a layer to the LSTM can increase the model's accuracy.

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