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Sentiment Analysis of Hotel Reviews With LSTM And ELECTRA

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Abstract: This study examines the importance of hotel review data analysis and the use of Natural Language Processing (NLP) technology in predicting hotel review sentiment. In this study, deep learning models such as Long Short-Term Memory (LSTM) and Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA) are used to predict hotel review sentiment in Indonesian. Hotel review data was obtained through a data scraping process with webscraper.io from the Tripadvisor website and a total of 977 hotel review data were obtained from a hotel in North Sumatera, Indonesia. Before the sentiment prediction process is carried out, hotel review data must go through the text preprocessing stage to remove punctuation marks, capital letters, stopwords, and a lemmatizer process is carried out to facilitate further data processing. In addition, sentiments that were previously unbalanced need to be balanced through the undersampling process. The data that has been cleaned and balanced is then labeled as negative (0), neutral (1) and positive (2) sentiments. The test results show that the ELECTRA model produces better performance than the LSTM with an accuracy of 47% by ELECTRA and 30% by LSTM.

Keywords: Sentiment Analysis; *Natural Language Processing (NLP); ELECTRA; LSTM; Data Scraping*

INTRODUCTION

This study focuses on sentiment analysis of hotel reviews using Google's Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA) and the Long short-term memory (LSTM) algorithm, as described in previous studies Electra is a model used to perform language processing, developed by Google. The LSTM algorithm is a Deep Learning algorithm that is used to process data sequentially, according to the context.(Clark et al., 2020) Hotel Review Prediction itself is a process for determining hotel ratings from the meaning contained in the text. In the context of hotel reviews, sentiment analysis can be used to determine whether the review is positive, negative or neutral towards the hotel. Studies related to the combination of Electra and the LSTM algorithm show that it can improve performance. By combining Electra and LSTM, this research is expected to produce a more accurate sentiment analysis of hotel reviews.(Arora et al., 2022)

Then the latest contribution to this research is in the form of sentiment analysis of hotel reviews in Indonesia which focuses on review sentiment analysis of hotels located in Medan, namely the Grand Mercure Maha Cipta Medan Angkasa obtained from a hotel and tourism site called tripadvisor.com. Previously, sentiment analysis of hotel reviews was generally carried out on datasets originating from various sites such as Agoda (Sambas et al., 2022), Traveloka (Cendani et al., 2023), Google Map (Sambas et al., 2022), and Tripadvisor (Baskoro et al., 2021). Various algorithms that have been researched include Random Forest (Utami, 2021a), Convolutional Neural Network (Kusumaningrum et al., 2021a), Long Short-Term Memory (LSTM) (Priyantina & Sarno, 2019), dan Reccurent Neural Network (Utami, 2021a). This research itself will use the LSTM algorithm because it has been widely

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used for processing text data. This research will examine the Tripadvisor website but this research focuses specifically on researching the Grand Mercure Maha Cipta Medan Angkasa hotel which has never been studied specifically before.

LITERATURE REVIEW

Various algorithms that have been studied include Random Forest, Convolutional Neural Network, Long Short-Term Memory (LSTM), and Recurrent Neural Network. This research itself will use the LSTM algorithm because this algorithm has been widely used to process text data. Thus the title of this study is SENTIMENT ANALYSIS OF HOTEL REVIEWS ON TRIPADVISOR WITH LSTM AND ELECTRA.(Jayanto et al., 2022)

METHOD

This study will conduct an experimental analysis using hotel reviews collected from Tripadvisor.com on the Grand Mercure Maha Cipta Medan Angkasa Hotel using webscrapper.io. Then, the data is processed with ELECTRA and the LSTM algorithm is used to classify the sentiments of the hotel reviews. (Bayu Baskoro et al., 2021)

(1) Data Collection

The dataset used in this study was obtained from Tripadvisor.com on the Grand Mercure Maha Cipta Medan Angkasa hotel page. This research uses webscrapper.io to collect the data in January 2023 with a total of 977 reviews.

(2) Long Short-Term Memory

LSTM (Long Short-Term Memory) is a type of artificial neural network used in natural language processing. LSTM can remember long information over long periods of time, so it can be used to process sequential data such as text or voice. LSTMs have a number of "cells" that are used to store information retrieved from input and control the flow of information through the network.

(3) Process with Naïve Bayes Classifier Algorithm

ELECTRA (Efficiently Learning an Encoder that Classifies Token Replacements Accurately) adalah sebuah model pembelajaran mesin yang dikembangkan oleh Google. Model ini didesain untuk menangani masalah pembelajaran dari contoh yang digunakan untuk melatih model. Model ini menggunakan teknik "self-supervised" yang memungkinkan model untuk belajar dari data yang tidak dilabeli. Dalam teknik ini, model ditugaskan untuk mengekstrak fitur dari suatu data yang diacak dan kemudian menentukan apakah fitur tersebut diambil dari data asli atau dari data yang diacak. Dengan cara ini, model dapat belajar dari data yang tidak dilabeli dan meningkatkan kemampuannya dalam mengekstrak fitur yang relevan dari data. Selain itu kombinasi ELECTRA dan LSTM telah diteliti pada penelitian sebelumnya dan menghasilkan peningkatan akurasi.

(4) Flow of Research Methods

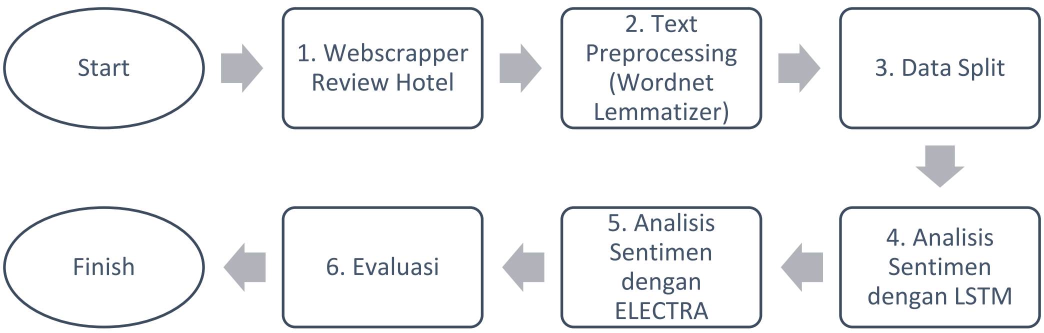

Figure 1. Flowchart of Research Methods

The flow of the research method is carried out according to the flowchart as shown in the image above, including:(Utami, 2021a)

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a) Webscrapper Hotel Review: In this stage, the review data for the Grand Mercure Maha Cipta Medan Angkasa hotel obtained through the Webscrapper on tripadvisor.com will be inputted into the system and divided into two types of data, namely Train Data, Validation Data, and Test Data.
b) Text Preprocessing: After the data is input, the data will be cleaned with Wordnet Lemmatizer which converts existing words into basic words.
c) Data Split: Data that has been preprocessed is then divided into training data, validation, and test data to ensure accurate analysis results.
d) Sentiment Analysis with LSTM: performs sentiment analysis using the Long-Short Term Memory (LSTM) technique, which is used to predict sentiment from hotel reviews.
e) Sentiment Analysis with ELECTRA: perform sentiment analysis using the Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA) technique, which is used to predict sentiment from hotel reviews.
f) Evaluation: Evaluate the results of the two sentiment analysis techniques to compare the quality of the results of each technique and choose the best technique to be used in research.

RESULT

Table 1. Feature Description

Column Name	Data Type	Description
reviewid	number	Unique identifier for each review
rating	number	Rating given by the reviewer, from 1 to 5
title	text	Title of the review
review	text	Text of the review
review_date	text	Date the review was posted
stay_date	text	Date the reviewer stayed at the hotel
trip_type	text	Type of trip the reviewer took (if specified)
room_tip	text	Tip for specific rooms (if specified)

The stages of web scraping hotel reviews via tripadvisor.com are carried out using webscraper.io, a tool that helps retrieve data from websites. In this stage, the hotel reviews collected come from the tripadvisor.com site and only focus on the Grand Mercure Maha Cipta Medan Angkasa (GMMCMA). After retrieving the data, all the information obtained such as review date, rating, review text, and other data is collected and stored in the form of a CSV (Comma Separated Value) file to be entered into the Jupyter Notebook program in the Dataframe format as shown above and produces a 977 GMMCMA hotel review data.

Figure 3. Hotel Review Rating Before Processing

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In this study, hotel review data is divided into 5 ratings as shown in the previous figure, with the highest number of ratings at number 50 and the lowest rating at number 10. However, making predictions with 5 ratings proves to be difficult and there is also a lack of data at low ratings. Therefore, in this study the rating review which is the dependent variable will be divided into 2 categories or what is commonly called the Binary Classification, namely Negative for ratings of 10-20, Neutral for ratings of 30 and Positive for ratings of 40-50. From these data, it was found that there were 225 reviews that were in the Negative category and 134 reviews that were in the Good category. This data transformation is very helpful in making predictions and facilitating the interpretation of the results of the research.

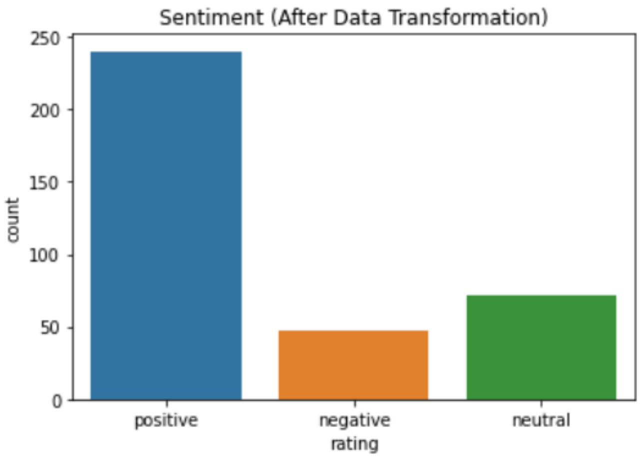

Figure 4. Hotel Review Rating After Processing

Thus, the independent and dependent variables in this study are as follows:

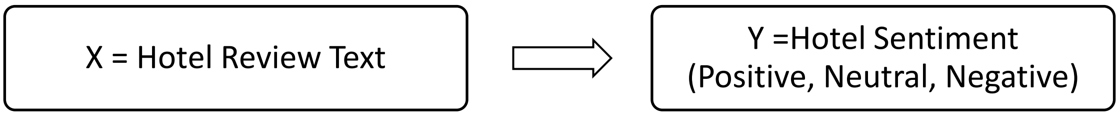

Figure 5. Research Variables Examined

Text Preprocessing

Text processing is an important part of the hotel rating prediction process, because it can affect the final result of the analysis. In the text processing process, text data will be processed to remove irrelevant information and improve data quality. In the process of text processing, several actions are performed such as:(Kusumaningrum et al., 2021b)

1) Remove punctuation and make text lowercase
2) Remove stopwords like "the", "and", "a", "to", etc
3) Doing lemmatization by modifying words into basic forms (lemma) such as "relaxed" becomes "relaxed"

The results of the text after going through the text processing process are cleaner and have more relevant and concentrated information as shown in the following figure.

Before Text Preprocessing:
Front office staff was very helpful and kind. Fast check in and also check out. The bellman was very helpful too, that was great to be here. Big lobby, and its very comfort area, i can relax for a while and have my qtime for myself. Next week i will coming again to this hotel, great hotel in Medan! but im very dissapointed about the break-fast, its not a five star standart, so so!

After Text Preprocessing:
front office staff helpful kind fast check also check bellman helpful great big lobby comfort area relax qtime next week come hotel great hotel medan im dissapointed breakfast five star standart

Figure 6. Text Pre-processing

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After the text data cleaning process, the number of sentiments in the resulting data is often unbalanced, where the number of positive or negative sentiments tends to be more than the number of neutral sentiments. Therefore, it is necessary to carry out an undersampling process to reduce the amount of data with dominant sentiments, so that each sentiment has a balanced amount of data. In addition, the sentiment in the data also needs to be represented numerically, such as 0 for negative sentiment, 1 for positive sentiment, and 2 for neutral sentiment. By using this technique, the sentiment classification process can be carried out more effectively and accurately.

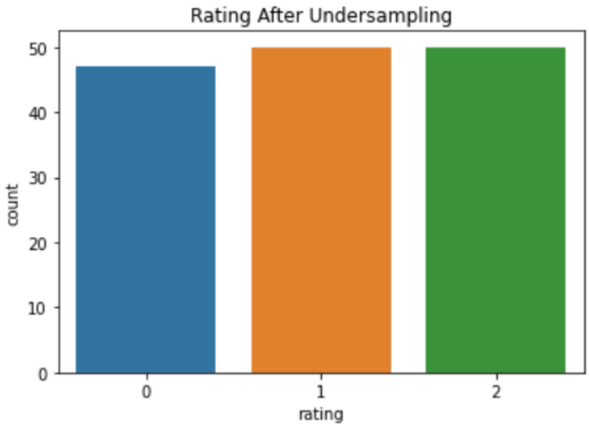

Figure 7. Rating Comparison After Undersampling

Data Split

In this study, the data used is divided into three different parts, namely training data, validation data, and test data. Train data is 60% of the total data, validation data is 20%, and test data is 20%. This aims to ensure that the built model can work well with new data. Train data is used to build the model, validation data is used to optimize the model, and test data is used to evaluate model performance. By sharing this data, we can ensure that our model performs well and is reliable in real situations.

Prediction Results

Prediction Results with LSTMA In the process of predicting hotel reviews in this study, LSTM requires the Tokenizer method to process text data. LSTM requires a tokenizer to break down the text data into a number of tokens that can be processed by the LSTM model. Tokens can be words, characters, or other parts of text. In this case, the tokenizer helps convert the text data into a numeric form that can be processed by the LSTM. Thus, the tokenizer helps LSTMs understand text data as a collection of related and meaningful tokens. After the data is processed with the Tokenizer, the LSTM goes through a training process with data train and validation, resulting in training accuracy as shown in the following table.

Table 1. LSTM and ELECTRA Accuracy Performance

	Training Los s	**Training Accuracy**	**Validation Loss**	**Validation Accuracy**
LSTM	68,84%	32,18%	68,75%	43,33%
ELECTRA	56,44%	54,37%	58,10%	66,67%

This table above shows the training results for two different models, LSTM and ELECTRA. The models were trained on a dataset and their performance was measured by training loss, training accuracy, validation loss, and validation accuracy. For the LSTM model, the training loss was 68.84%, which means that during training, the model was not able to correctly predict the output about 68.84% of the time. The training accuracy was 32.18%, which means that the model was able to correctly predict the output about 32.18% of the time during training. For the validation set, the model had a validation loss of 68.75%, indicating that it did not perform well in predicting the output for the

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validation set. The validation accuracy was 43.33%, which means that the model was able to correctly predict the output about 43.33% of the time for the validation set.

On the other hand, for the ELECTRA model, the training loss was 56.44%, indicating that it performed better during training compared to LSTM. The training accuracy was also higher at 54.37%, meaning that the model was able to correctly predict the output about 54.37% of the time during training. For the validation set, the model had a validation loss of 58.10%, which is slightly higher than the training loss, but still performed better than LSTM in predicting the output for the validation set. The validation accuracy was 66.67%, indicating that the model was able to correctly predict the output about 66.67% of the time for the validation set, which is also higher than LSTM.

Table 2. LSTM and ELECTRA Testing Classification Report

Metric	LSTM	ELECTRA	Description
Accuracy	0.30	0.47	The proportion of correctly classified instances out of the total number of instances. LSTM has an accuracy of 0.30, while ELECTRA has an accuracy of 0.47, indicating that ELECTRA performed better at classifying instances correctly.
Precision	0.38-0.40	0.33-0.56	The proportion of true positives (correctly classified instances) out of all positive predictions. LSTM has a precision range of 0.38-0.40, while ELECTRA has a precision range of 0.33-0.56, suggesting that LSTM performed slightly better at correctly identifying positive instances.
Recall	0.29-0.50	0.38-0.62	The proportion of true positives (correctly classified instances) out of all actual positive instances. LSTM has a recall range of 0.29-0.50, while ELECTRA has a recall range of 0.38-0.62, indicating that ELECTRA performed better at correctly identifying actual positive instances.
F1-Score	0.28-0.33	0.35-0.59	The weighted average of precision and recall, where 1 is the best possible score and 0 is the worst. LSTM has an F1-score range of 0.28-0.33, while ELECTRA has an F1-score range of 0.35-0.59, indicating that ELECTRA outperformed LSTM in terms of overall classification accuracy.

Based on the testing results above, ELECTRA performed better than LSTM in accurately classifying instances, achieving an accuracy of 47% compared to LSTM's accuracy of 30%. However, LSTM performed better in identifying positive instances, while ELECTRA performed better in identifying actual positive instances. In terms of overall classification accuracy (F1-score), ELECTRA outperformed LSTM.

The Importance of Rating Review Prediction Analysis

Hotel review sentiment analysis is very important because it provides information about the level of satisfaction of guests staying at the hotel. This is very useful for hotel managers to improve the quality of their services and meet guest needs. Sentiment analysis is also useful for providing recommendations for guests who want to find information about a particular hotel.

Research Contribution with New Datasets

This study focuses on sentiment analysis of hotel reviews using Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA) and the Long short-term memory (LSTM) algorithm. The combination of Electra and LSTM is expected to produce a more accurate sentiment analysis compared to using only one algorithm.(Morama et al., 2022) In addition, this study also focuses on sentiment analysis of hotel reviews Grand Mercure Maha Cipta Medan Angkasa, which is a new hotel dataset of 977 data that has not been specifically studied before.(HaCohen-Kerner et al., 2020)

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Comparison of LSTM and ELECTRA

Based on the evaluation results of the two models, it can be said that the ELECTRA model has better performance than the LSTM model in terms of predicting sentiment in hotel review text data. This can be seen from the results of training and validation accuracy in each model. The ELECTRA model has an accuracy of 47% while the LSTM model only has an accuracy of 30%. Another advantage of the ELECTRA model is that it does not require a tokenizer process like the LSTM model. This speeds up the data processing process and gives better results.(Divya et al., 2020)

DISCUSSIONS

Based on the evaluation results of the two models, it can be said that the ELECTRA model has better performance than the LSTM model in terms of predicting sentiment in hotel review texts. This can be seen from the training results and validation accuracy in each model. The ELECTRA model has an accuracy of 47% while the LSTM model only has an accuracy of 30%. Another advantage of the ELECTRA model is that it does not require a tokenizer process like the LSTM model. This speed up the data processing process and gives better results.

CONCLUSION

Analysis of hotel review predictions on the Grand Mercure Maha Cipta Medan Angkasa hotel obtained from Tripadvisor provides accurate and useful information for hotel managers. Hotel review predictions can help hotel managers to find out how their guests rate the quality of hotel services and facilities. This information can help hotel managers to determine corrective actions to meet guest needs and expectations. In this study, the LSTM and ELECTRA models have been used to predict hotel reviews in Indonesian.(Yao, 2022) The results of the analysis show that the LSTM model has a fairly good performance, but is still less effective in predicting hotel reviews with an accuracy of 30%. Meanwhile, the ELECTRA model has better performance with an accuracy of 47%. This shows that ELECTRA has the potential to improve the effectiveness of predicting hotel reviews compared to LSTM.

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