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Aspect-Based Sentiment Analysis on Hotel Reviews Using Gated Recurrent Unit

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Abstract

The rapid growth of online platforms has enabled users to share their experiences about various products and services, including hotels. Hotel reviews are crucial in understanding customer perceptions and preferences in the tourism sector. Tiket.com, a web and mobile-based online travel agent, allows users to book hotels and submit reviews, which can be positive, negative, or neutral. These reviews provide valuable insights into the strengths and weaknesses of hotel services and can serve as evaluation material for improvements. This study extracts meaningful information from user reviews through an aspect-based sentiment analysis approach. It categorizes sentiments into specific aspects such as price, cleanliness, service, location, and facilities, ensuring the feedback is more structured and actionable. The research utilizes a Gated Recurrent Unit (GRU) model combined with fastText word embedding to analyze sentiment. A dataset of 6512 hotel reviews was collected through web scraping. The resulting model achieved an accuracy of 91% and was evaluated using a confusion matrix. The approach enhances understanding of customer satisfaction by presenting sentiments based on targeted service aspects, making the analysis more concise and relevant for hotel management.

Keywords: FastText; Gated Recurrent Unit; Confusion Matrix Introduction

INTRODUCTION

The hospitality business provides temporary lodging to visitors. This business is also part of tourism, one of the important economic sectors for many countries worldwide. In an increasingly advanced digital era, more and more people are using the internet to find information about hotels before traveling. Hotel reviews and reviews from other users become a valuable source of information for potential travelers when determining the right choice of accommodation. However, the large volume of reviews continues to increase, and it is a challenge for hotel companies to extract information about their hotels from these reviews (Normasari, 2013).

Currently, people are given the convenience of providing opinions in the form of reviews/comments about something to help others, especially tourists, find the place they want to see anywhere and anytime by relying only on an internet connection. Travelers can easily get an idea when staying at an inn by reading reviews/comments widely circulated on social networks and websites, especially online ticket booking applications. The access rights given to customers are provided and can be used easily and conveniently when customers want to give opinions, criticisms, and suggestions in the application review section. Customer satisfaction is shown from the positive reviews on price, cleanliness, service, location, and facilities.

However, hotels often find it challenging to understand reviews due to the variety of user reviews (Samsidar, 2017). To understand the review, sentiment analysis can be done based on aspects that can determine the sentiment of a review. This analysis is done by obtaining hotel review data from the tiket.com site. Classification of sentiment on aspects by determining opinions formed from elements of an entity into positive, negative, or neutral categories (Faris Zharfan Alif, 2020).

In classifying sentiment based on aspects, the author uses the Gated Recurrent Unit (GRU) algorithm in this research. The Gated Recurrent Unit is a development method derived from the Recurrent Neural Network (RNN) to provide results for each recurrent unit to capture relationships (dependencies) on different time scales and be adaptive. This method is used because it can provide high enough accuracy results in the classification category that previous researchers have done entitled Sentiment Analysis of Chinese Product Reviews using Gated Recurrent Units by Jun Sheng Lee (2019) with an accuracy of 87.9%.

RESEARCH METHOD

Text Preprocessing

Text preprocessing is a process carried out to store structured textual data in a database by converting unstructured textual data first into structured data (Langgeni et al., 2010). Text processing is also one of the text mining techniques. The correct text processing technique is used to help a Machine Learning model have better quality (Nayak & Kanive, 2016).

In this text preprocessing stage, the data that has been processed will be prepared to enter the next stage by producing structured words. This research applies the stages of text preprocessing, namely cleaning, case folding, punctual removal, normalization, stopward removal, stemming, and tokenization. The data is sourced from the tiket.com online hotel ticket booking application by passing the data scrapping process.

Sentiment Analysis

Sentiment analysis is a technique used to determine the opinions of the public on specific subjects obtained from data sets. Sentiment analysis is also a technique that analyzes a person's views, attitudes, evaluations, sentiments, and emotions in written form. Sentiment analysis is one of the techniques used for research and is widely studied in data mining and text mining (Liu, 2012).

Sentiment analysis analyzes several words and sentences often seen in comments, feedback, or criticism columns that indicate achieving various goals. (Prabowo & Thelwall, 2009). There are three categories in sentiment analysis: positive, negative, and neutral. In other words, sentiment analysis can be interpreted as classifying sentiments into existing categories.

Sentiments categorized as positive are denoted by (1), which means statements containing approval and feelings of pleasure. Sentiments categorized as negative are denoted by (-1), which means statements containing anger, disappointment, and rejection. Meanwhile, sentiment categorized as neutral is denoted by (0), meaning that the statement does not fall into either the positive or negative sentiment category (Ferdiana et al., 2019).

Aspect-Based Sentiment Analysis (ABSA)

Aspect Sentiment Analysis (ABSA) is a subarea of opinion mining that allows obtaining information about user-defined aspects based on review mining. ABSA is also a method used to process continuous analysis of sentiment analysis and maximize performance in sentiment analysis. In addition, Aspect Sentiment Analysis (ABSA) is also used to analyze the unstructured text, which is then divided and grouped into several aspect categories: positive sentiment, negative sentiment, and neutral sentiment categories (Pontiki et al., 2016).

In Aspect Based Sentiment Analysis (ABSA), comments and opinions given by a person will be analyzed and divided into positive, hostile, and neutral sentiment value categories. ABSA is also done because it focuses more on details (Liu, 2012). Things that are considered in Aspect Based Sentiment Analysis (ABSA), for example, in the hotel review sentence, "the price is very affordable with many facilities that can be used, but the location is far and not close to anywhere." The review sentence can be analyzed in that the price and facilities indicate approval and pleasure, which can be grouped into positive sentiments. Still, the following review sentence states a negative sentence with a remote location and can be grouped into negative sentiments.

Tiket.com

Tiket.com is one of the companies engaged in tourism and acts as an online travel agent based on applications and websites that can be accessed by desktop and mobile. The company was founded in August 2011 and is based in Indonesia. Tiket.com is also considered one of the OTA (Online Travel Agency) pioneers in Indonesia from ticket sales, one of which is hotel tickets. tiket.com users can book hotel tickets that are accessed in real time with an internet connection anywhere and anytime. In 2018, tiket.com was officially designated as the Official Partner of the Indonesian Ministry of Tourism and Creative Economy.

Tiket.com allows consumers to easily book hotel rooms in Indonesia and abroad, such as Singapore, Hong Kong, South Korea, etc. In this study, only user reviews included hotel reviews in the tiket.com application. Users can provide reviews with an unspecified character length in the tiket.com review column, which hotel companies can use as an improvement and increase hotel guest satisfaction.

Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) is one of the artificial neural network architectures used to process data sequentially. In other words, textual data processing and Natural Language Processing often use RNN because the data has a sequential form.

The function of RNN is to store and retain information and memory used in the past by repeating its architecture. This is done to sufficiently recognize the data patterns that have been formed and then be able to make predictions accurately.

The input given in the RNN architecture at each stage is the output or calculation results obtained from the previous stage, and is repeated until the last data. The following is the general architecture of an RNN.

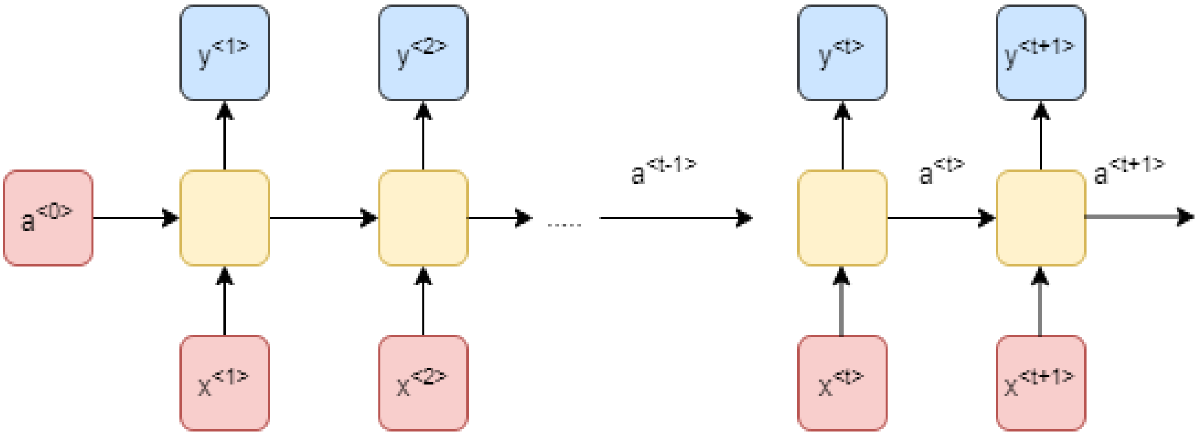


Fig 1: Architecture of Recurrent Neural Network (Amidi, 2018)

In the figure above, each time (t) has an input which is x<t>, with an activity function symbolized by a<t> and an output which is y<t>. In RNN, problems that often occur are exploding gradients and vanishing. This is because RNN has many layers that make the gradient value smaller during the training process, so the value approaches zero or disappears. An exploding gradient can occur when the gradient value has large amount. Thus, to solve these problems, the Long Short-Term Memory and Gated Recurrent Unit algorithms can be used.

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is an evolution of the Recurrent Neural Network (RNN) architecture that researchers continuously use because it has the advantage of organizing memory for each input using memory cells and gate units. LSTM can also overcome the vanishing gradient, which is the weakness of RNN. The following is the architecture of LSTM.

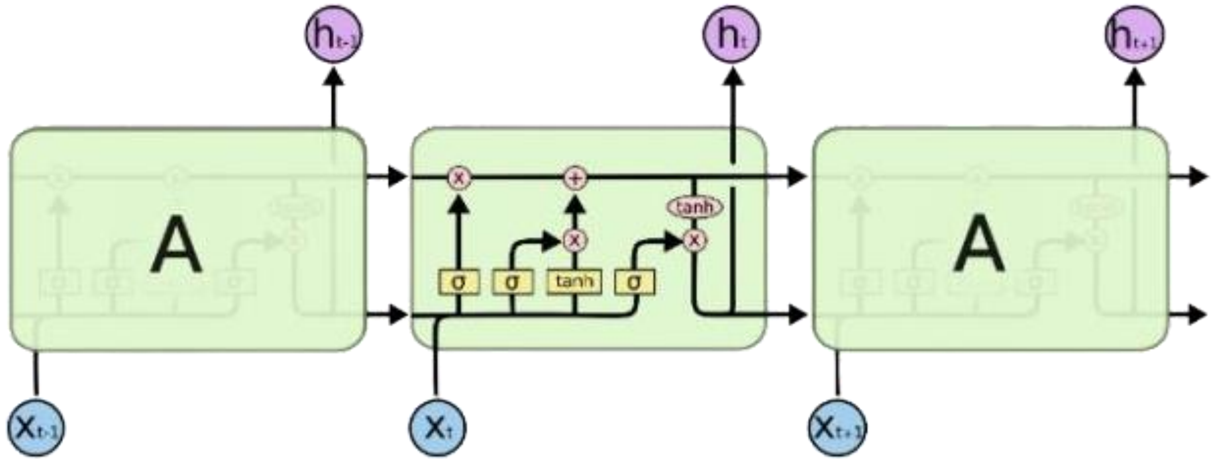


Fig 2 Architecture of LSTM (Aldi & Aditsania, 2018)

The figure above explains the workflow of memory cells when LSTM works on each neuron. Gate units are several activation function processes on each input on neurons, including forget gate, cell state, input gate, and output gate.

Input data information at the forget gate will be processed, and the data will be stored or data that will be discarded in memory cells. The sigmoid activation function is the activation function used in the forget gate. Where the output results are between 0 and 1. If the output is zero, all data will be discarded, and vice versa. If the output is 1, then all data will be stored. Here is the formula used:

$f_t = \sigma (W_f . [h_{t-1}, x_t] + b_f)$ (2.1) Information:

f_t = forget gate

σ = sigmoid activation function

W_f = weight

h_{t-1} = previous hidden state

x_t = input

b_f = bias

Two gates will be performed in the input gate. First, the gate will decide the value to be updated using the sigmoid activation function. Second, the memory cell will store the activation function to create a new value vector.

The state cell will update the value in the memory cell. This value is obtained by combining the values in the forget and input gates. The following formula will be used:

$i_t = \sigma (W_i . [h_{t-1}, x_t] + b_i)$ (2.2)

$\check{C}_t = \tanh (W_c . [h_{t-1}, x_t] + b_c)$ (2.3)

$C_t = f_t * C_{t-1} + i_t * \check{C}_t$ (2.4) Information:

I_t = gate input

$\check{C}_t$ = candidate cell state

C_t = cell state

h_{t-1} = hidden state before tanh = tanh activation function

W_i, W_c = weight on input gate and cell state b_i, b_c = gate and cell state input bias

Two gates exist in the output gates and will be implemented, namely by using the sigmoid activation function; the value will be decided in the memory cell section, and then by using the tanh activation function, the value will be placed in the memory cell. Furthermore, the output value is generated by multiplying the two gates. The formula that will be used is as follows.

$o_t = \sigma(W_o \,.\, [h_{t-1}, x_t] + b_o)$ (2.5) $h_t = o_t * tanh(C_t)$ (2.6)

Information:

o_t = output gate h_t = hidden state

W_o = weight output gate

b_o = bias value

Gated Recurrent Unit

The gated Recurrent Unit was first introduced by Chung et al. (2014), which was developed from LSTM. GRU was formed to capture dependencies by utilizing each recurrent unit at different times according to its adaptation. GRU has an information flow regulator component grouped into reset and update gates. The Reset gate will decide to combine new input with past information, while the update gate will decide on the amount of past data that must still be stored. Each gate uses the sigmoid activation function to output 0 - 1. The gate will close the data when the output is close to 0 and permit the data to continue to the next step if the output is close to 1. The following is the architecture of the reset gate and update gate.

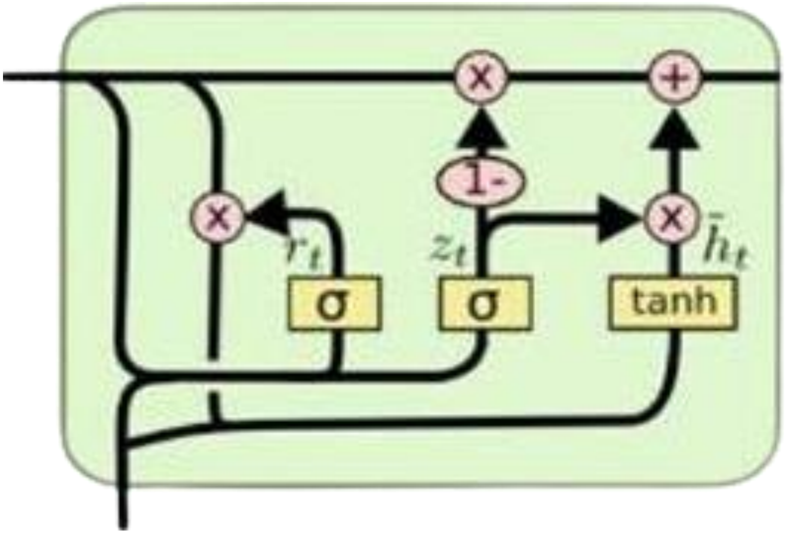


Fig 3 Architecture of GRU (Caniago et al., 2021)

$z_t = \sigma(W_z X_t + U_z h_{t-1} + b_z)$ (2.2)

$r_t = \sigma(W_r X_t + U_r h_{t-1} + b_r)$ (2.3)

$\tilde{h}_t = tanh\ (W_h X_t + U_h\ (r_t\ .\ h_{t-1}) + b_h)$

(2.4) Information:

zt = update gate

rt = reset gate

$\tilde{h}t$ = candidate value

htt = output or hidden state

ht-1 = output state before

σ = sigmoid activation function

tanh = tanh activation function

Xt = input

Ur = reset weight that has a connection with the output before

Uh = candidate weight that has a connection with the production before

Uz = update weight that has a connection with the previous output

br, bz, bh = bias parameters

Wz, Wr, Wh = weight parameters

Word Embedding

Word embedding is a method used to map text data into vectors. Word embedding must be done because neural network models can only process numerical data. In this stage, a library is required, namely fastText, introduced by Facebook, which helps handle words that have never been found before.

RESULT & DISCUSSION

Model Implementation

In conducting model training, the author changed the hyperparameter tunning in several trials to obtain a model with the best results and performance. The author conducted training with different batch sizes, neuron units, and epochs. The training process with various epochs can be seen in Table 1.

Table 1 Training with Hyperparameter Changes Accuracy

Batch Size	Unit Neuron	Epoch	Aspect Validation Accuracy				
			Price	Cleanliness	Services	Location	Facilities
64	8	10	0.79	0.5	0.6	0.7	0.77
64	32	10	0.89	0.8	0.8	0.84	0.79
64	64	10	0.88	0.92	0.84	0.89	0.83
64	8	20	0.92	0.84	0.80	0.75	0.78
64	32	20	0.96	0.9	0.9	0.94	0.85
64	64	20	0.94	0.89	0.84	0.87	0.86
64	8	30	0.81	0.63	0.81	0.80	0.81
64	32	30	0.93	0.92	0.91	0.92	0.86
64	64	30	0.94	0.93	0.87	0.90	0.85
32	8	10	0.85	0.67	0.74	0.74	0.78
32	32	10	0.89	0.88	0.82	0.87	0.8
32	64	10	0.93	0.91	0.87	0.93	0.84
32	8	20	0.85	0.78	0.82	0.82	0.77
32	32	20	0.91	0.93	0.87	0.92	0.84
32	64	20	0.94	0.94	0.9	0.9	0.85
32	8	30	0.9	0.84	0.83	0.81	0.78
32	32	30	0.92	0.9	0.88	0.8	0.86
32	64	30	0.94	0.94	0.87	0.8	0.85

Table 2 Training with Hyperparameter Loss Changes

Batch Size	Unit Neuron	Epoch	Loss Validation Aspek				
			Price	Cleanliness	Services	Location	Facilities
64	8	10	0.55	0.98	0.92	0.76	0.71
64	32	10	0.29	0.52	0.51	0.42	0.53
64	64	10	0.29	0.32	0.43	0.31	0.46
64	8	20	0.45	0.64	0.55	0.65	0.62
64	32	20	0.19	0.24	0.28	0.18	0.4
64	64	20	0.25	0.27	0.41	0.28	0.39
64	8	30	0.46	0.76	0.58	0.51	0.54
64	32	30	0.13	0.22	0.43	0.32	0.38
64	64	30	0.16	0.25	0.40	0.32	0.36
32	8	10	0.37	0.74	0.7	0.63	0.61
32	32	10	0.27	0.36	0.5	0.39	0.49
32	64	10	0.19	0.28	0.4	0.24	0.43
32	8	20	0.35	0.56	0.48	0.46	0.58
32	32	20	0.23	0.25	0.41	0.3	0.45
32	64	20	0.15	0.22	0.41	0.28	0.4
32	8	30	0.27	0.45	0.45	0.54	0.56
32	32	30	0.16	0.2	0.43	0.33	0.39
32	64	30	0.17	0.23	0.45	0.34	0.4

Based on Table 1 and Table 2 for the hyperparameter tunning experiment above, it is obtained that the best parameter values are batch size, which is 64, neuron unit, which is 32, and epoch, which is 20. With this experimental process, the accuracy of aspect model validation is obtained at 91%, and the average loss is 26%. The results of the accuracy and loss graphs on price, cleanliness, service, location, and facilities for the best model can be seen in the figure below.

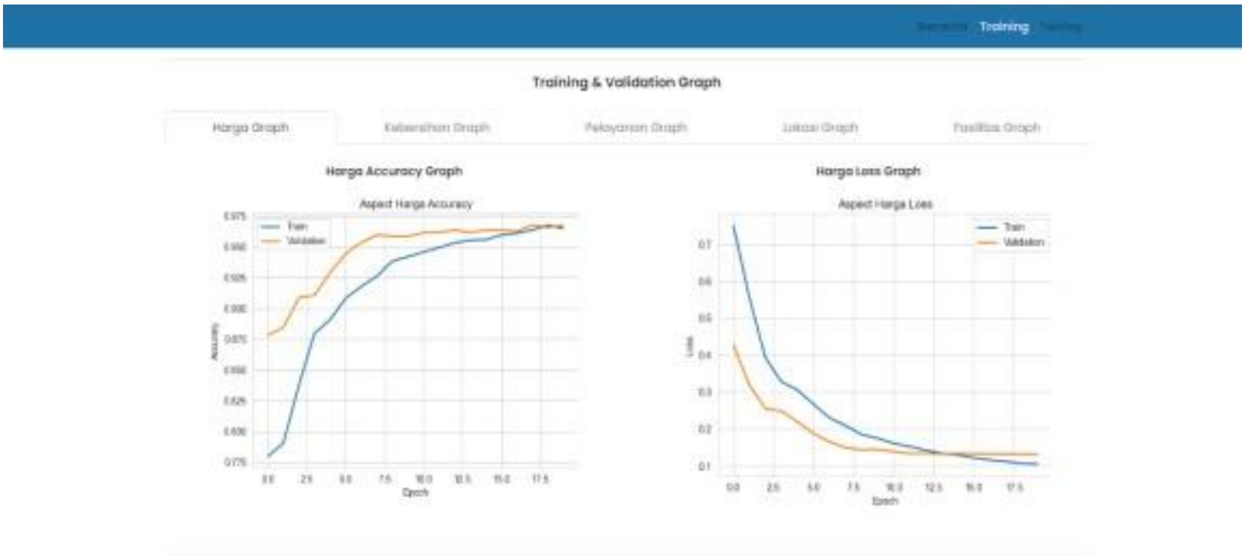


Fig 4 Accuracy and price aspect loss graph

Fig 4 Accuracy and price aspect loss graph In the figure above, the training and validation data for the price aspect show an accuracy rate of 0.96 with a loss value of only 0.19. This shows the performance of the best model.

Fig 5 Accuracy and cleanliness aspect loss graph

In the figure above, the training data and validation data for the hygiene aspect in the accuracy graph show a value of 0.9 and a loss of 0.24.

Fig 6 Accuracy and service aspect loss graph

In the figure above, the training and validation data of the service aspect in the accuracy graph is 0.9, and loss shows a value of 0.28.

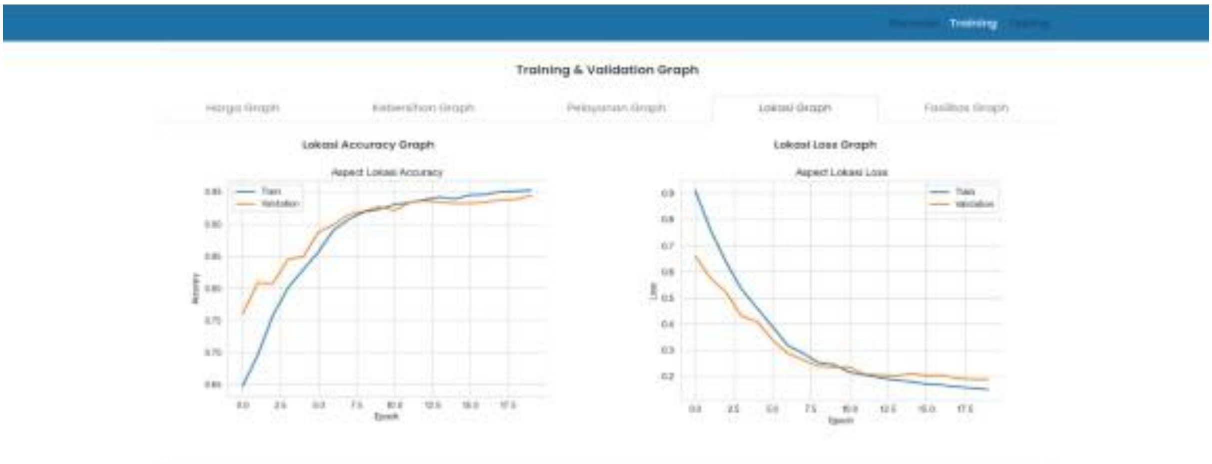


Fig 7 Accuracy and location aspect loss graph

In the figure above, the training and validation data for the location aspect show an accuracy rate on the graph of 0.94 and a loss of 0.18. The lower the loss value obtained, the better the performance.

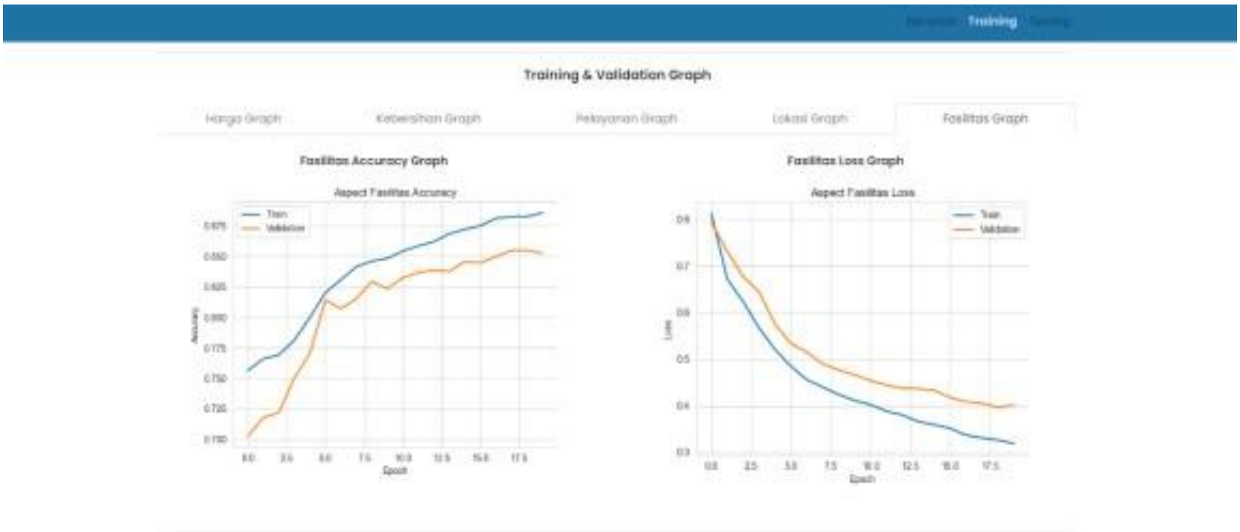


Fig 8 Accuracy and facilities aspect loss graph

In the figure above, the facility's training data and validation data aspects in the accuracy graph are 0.85, and the loss shows a value of 0.4. This is the highest value with the lowest loss at batch size 64, neuron unit 32, and epoch 20.

The dataset is then divided into training and validation data with a ratio of 80% for training data and 20% for validation data to be tested into the model. The preprocessing process consists of cleaning, case folding, punctual removal, normalization, stopword removal, stemming, and tokenization002E

Sentiment and Histogram Comparison The histogram displayed on the testing page illustrates the sentiment of the five aspects of each hotel. The histogram also provides a comprehensive view of customers' perceptions of price, cleanliness, service, location, and facilities. Thus, hotel companies can quickly evaluate customer reviews of these aspects and respond with necessary corrective actions. This allows companies to improve service quality, optimize prices, and fine-tune their facilities according to customer needs and expectations. This histogram becomes a handy tool in making data-driven decisions to improve customer satisfaction and hotel business competitiveness.

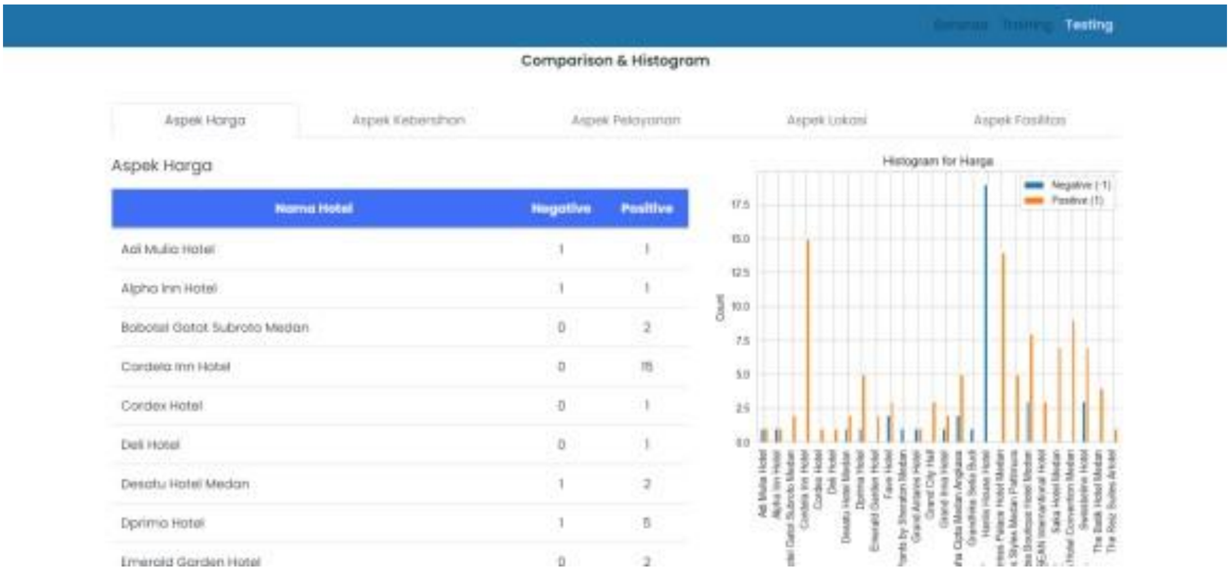


Fig 9 Result table and histogram of the price aspect

Based on Fig 9 above, it can be concluded that on the price aspect, most hotels get positive sentiments from the customer preprocess, with some hotels getting more positive feelings than negative. However, some hotels, such as Hanlis House Hotel and Caribbean Boutique Hotel Medan, get significant negative sentiments. Cordelia Inn Hotel and Hermes Palace Hotel Medan received highly positive sentiments.

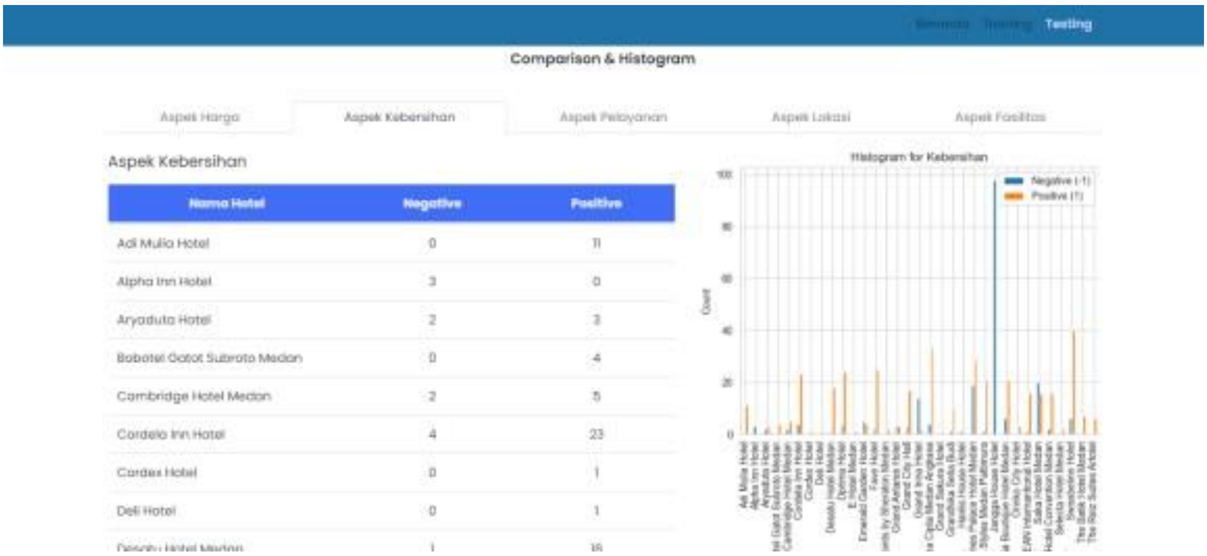
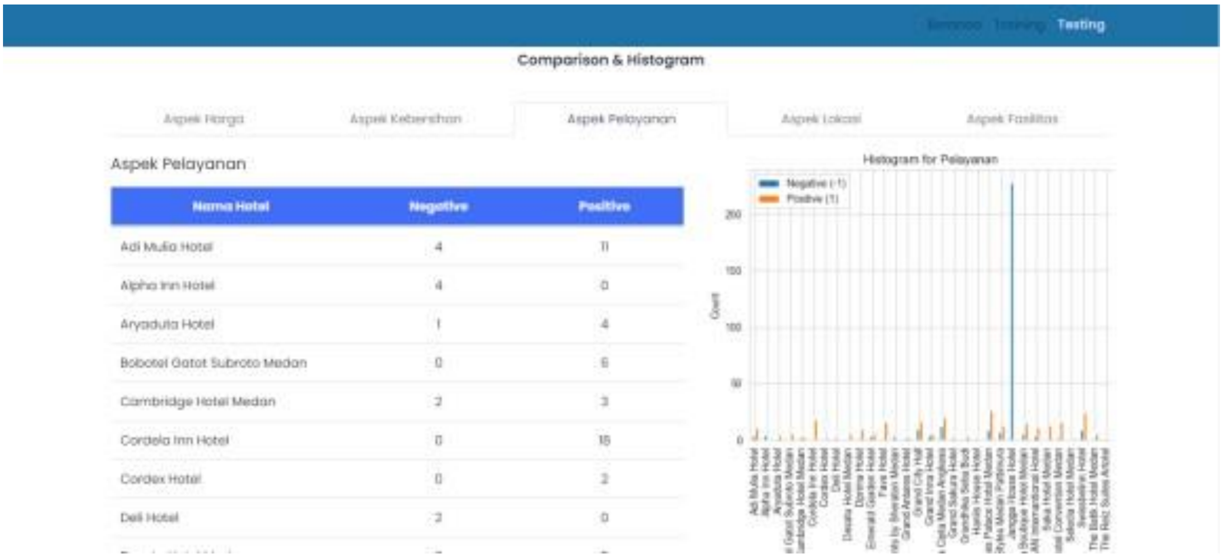


Fig 10 Result table and histogram of cleanliness aspect

The review data on the cleanliness aspect of various hotels shows significant variations in customer sentiment. Some hotels, such as Grand Mercure Maha Cipta Medan Angkasa and Swissbelinn Hotel, received positive sentiments, with most preprocesses complimenting the cleanliness. However, some hotels, such as Jangga House Hotel, received strikingly negative sentiments, indicating the need for improvement. Hotel managers need to focus on improving hygiene standards to increase customer satisfaction.



Nama Hotel	Negative	Positive
Adi Mulia Hotel	4	11
Alpha Inn Hotel	4	0
Aryaduta Hotel	1	4
Bobotel Gatot Subroto Medan	0	6
Cambridge Hotel Medan	2	3
Cordela Inn Hotel	0	15
Cordex Hotel	0	2
Deli Hotel	2	0

Fig 11 Result table and histogram of service aspect

Regarding service, customer review data for various hotels shows significant variations. Some hotels, such as Hermes Palace and Swissbelinn, received high praise for their positive service. However, hotels such as Jangga House Hotel also get significant negative sentiments regarding service.

Nama Hotel	Negative	Positive
Adi Mulia Hotel	1	6
Alpha Inn Hotel	0	1
Aryaduta Hotel	0	2
Bobotel Gatot Subroto Medan	0	3
Cambridge Hotel Medan	0	3
Cordela Inn Hotel	0	17
Cordex Hotel	0	3
Desatu Hotel Medan	0	19

Fig 12 Result table and histogram of location aspect

In the above aspect of location, customer review data on various hotels reflects a significant variation. Some hotels, such as Dprima Hotel and Caribbean Boutique Hotel Medan, received significant positive preprocesses regarding the location they offer. However, some hotels, such as Jangga House Hotel and Swissbelinn Hotel, receive negative sentiments regarding their location.

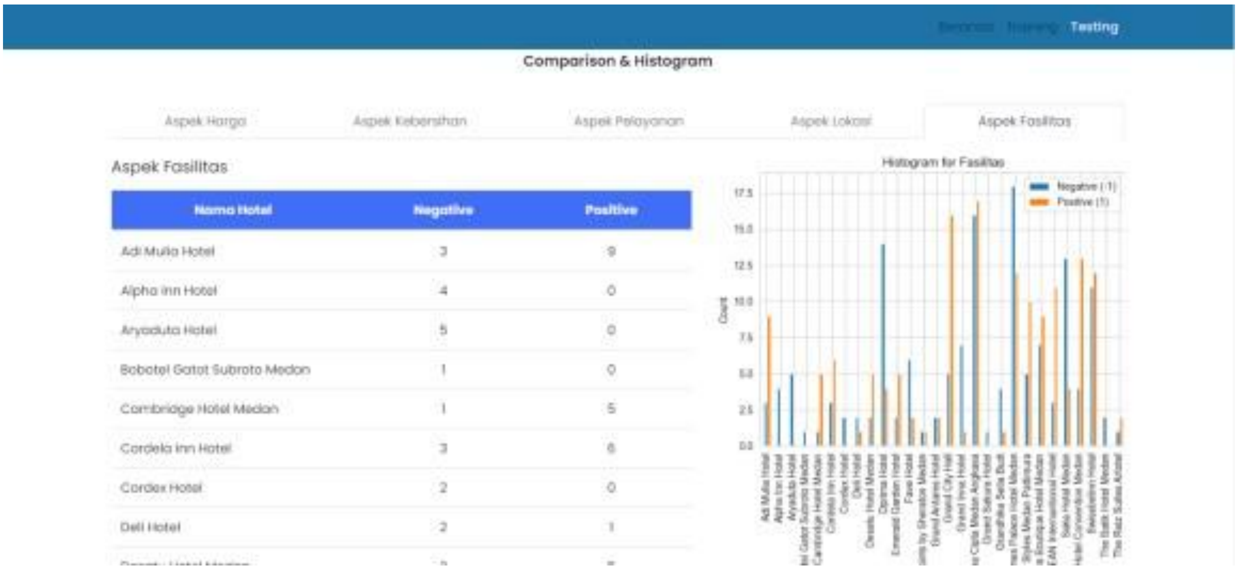


Fig 13 Result table and histogram of facilities aspect

In Fig 13 above, for the facilities offered, customer reviews describe diverse experiences at various hotels. Some hotels, such as Grand City Hall and Grand Mercure Maha Cipta Medan Angkasa, received high appreciation for their facilities, with many positive preprocesses. However, some hotels, such as Hermes Palace Hotel Medan, received negative sentiments about facilities. This shows that improving and maintaining hotel facilities is essential in ensuring a satisfying experience for guests. Most hotels need to pay attention to customer feedback to improve their facilities.

Model Evaluation

In this research, model evaluation is carried out using a confusion matrix to measure the performance of the classification model. A confusion matrix is a table that compares the model prediction with the actual value of the tested data. The confusion matrix will provide information about comparing the actual and predicted values using accuracy, precision, recall, and FI-score calculations. The confusion matrix on the price aspect is shown in Figure 14 below.

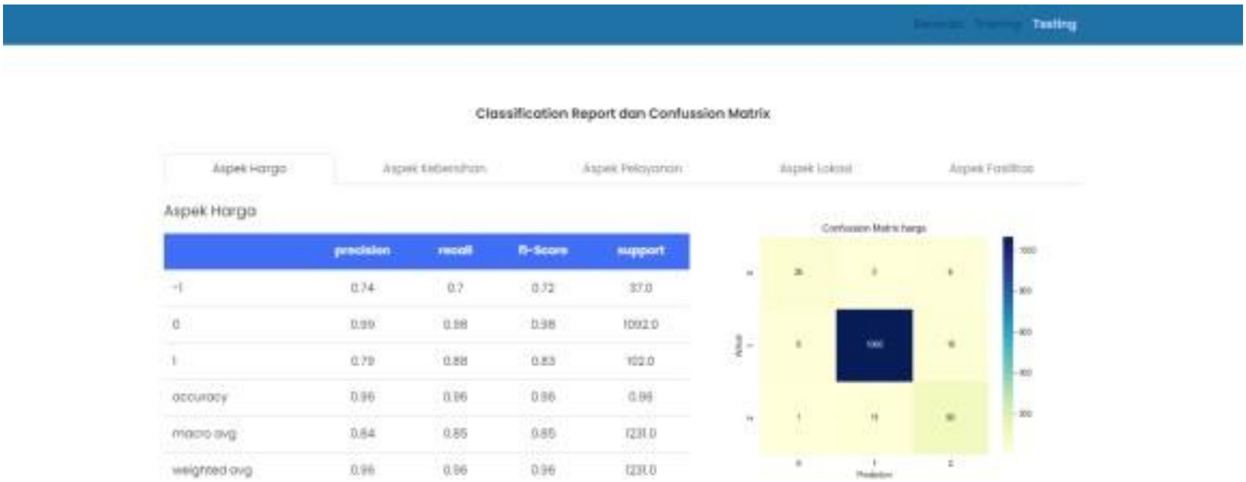


Fig 14 Confusion matrix of the price aspect

Fig 15 Confusion matrix of cleanliness aspect

Fig 16 Confusion matrix of service aspect

	precision	recall	f1-Score	support
-1	0.83	0.5	0.63	107.0
0	0.91	0.99	0.95	845.0
1	0.95	0.86	0.9	279.0
accuracy	0.92	0.92	0.92	0.92
macro avg	0.9	0.78	0.83	1231.0
weighted avg	0.92	0.92	0.91	1231.0

Fig 17 Confusion matrix of location aspect

	precision	recall	f1-Score	support
-1	0.74	0.72	0.73	145.0
0	0.92	0.92	0.92	938.0
1	0.66	0.66	0.66	148.0
accuracy	0.87	0.87	0.87	0.87
macro avg	0.77	0.77	0.77	1231.0
weighted avg	0.87	0.87	0.87	1231.0

Fig 18 Confusion matrix of facilities aspect

CONCLUSION

Produce performance with accuracy results in the price aspect of 96%, the cleanliness aspect of 90%, the service aspect of 90%, the location aspect of 92%, and the facility aspect of 87%. The average accuracy result of the five aspects is 91%. This provides insight into evaluating hotel visitors' reviews of hotel aspects, such as price, cleanliness, service, location, and facilities. Thus, GRU effectively performs aspect-based sentiment analysis tasks in the hospitality industry. The batch size of 64, the number of neuron units of 32, and the number of epochs of 20 were the parameters that resulted in the highest accuracy of 92%. Based on the comparison of positive and negative sentiment results on various hotels, some of the most superior hotels in sentiment are Grand Mercure Maha Cipta Medan Angkasa Hotel, especially in the aspect of cleanliness with the number of positive sentiments, as many as 33 reviews and Swissbelinn Hotel in the aspect of cleanliness with the number of positive sentiments as many as 40 reviews.

However, on the other hand, Jangga House Hotel received negative sentiments, especially regarding service, with 228 reviews. Likewise, Saka Hotel received. Based on the precision, recall, and F1-Score calculation on each aspect, the total accuracy value of 5 aspects is obtained with high negative sentiment, especially in the aspect of cleanliness, which has 20 reviews.

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