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Sentiment Analysis Based on Review of Puncak B29 Lumajang using Backpropagation Neural Network

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***Abstract*— Sentiment analysis is a method that applies the concept of text mining to provide a classification that has positive, negative or neutral polarity for each sentence or document. The problem formulation carried out in this research is the role of sentiment analysis in analyzing reviews of the Puncak B29 Lumajang tourist attraction based on user comments on Google Maps. This research was carried out in 3 stages, starting with data collection in the form of a review of the Google Maps application which was carried out by scrapping data, carrying out text preprocessing, including case folding, tokenizing, stopwords, and stemming and categorizing each review according to sentiment using the Backpropagatin Neural Network (BNN) classification method. Sentiment classification based on Puncak B29 reviews on Google Maps using Backpropagation Neural Network has the best accuracy, recall and F1-score evaluation results for a total of 50 iterations, each with an average value of 97.33%, 100.00% and 98.47%. Meanwhile, the best precision value for the number of iterations is 10 iterations, which has an average value of 99.72%. From this description, it can be concluded that the evaluation value will get better along with the number of iterations carried out throughout the classification process.**

Keywords—Sentiment Analysis, Text Mining, Puncak B29, Backpropagation Neural Network

I. Introduction

The development of internet-based technology has had an impact on the wider spread of innovation in various sectors, including industry, the economic sector and the tourism sector. This innovation is demonstrated by the creation of various products that have been marketed in various circles, the proliferation of content creators on various social media, and tourist attractions provided for visitors. Apart from that, through the use of technology, humans can easily search for and obtain information about these many innovations through internet search engines [1].

From the tourism sector, developments in internet-based technology can be used to dig up information about tourism spots and process existing data to measure quality through comparing visitors' opinions about a tourism spot [2]. The results of these quality measurements can be used as a consideration for users to determine decisions in choosing tourist attractions [3], and can be useful for tourism managers as evaluation material to improve the quality of these tourist attractions so that they can attract more visitors [4].

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Evaluation can be done by providing reviews and comments from users and visitors to tourist attractions. These reviews can be provided via the Google Maps API application. However, a large number of reviews will certainly be difficult and require a long time if you have to analyze each review manually [5]. Therefore, to analyze a large number of reviews, sentiment analysis techniques are used. Sentiment analysis is a method that applies the concept of text mining to provide a classification that has positive, negative or neutral polarity for each sentence or document [6]. This polarity is made as a reference for decision-making and as an evaluation for the future development of a tourist attraction [7].

Sentiment analysis uses various methods of classification to determine polarities from reviews or comments. Some research about sentiment analysis includes Backpropagation Neural Network (BNN) method [8], [9], [10], Naive Bayes Classification (NBC) method [11], [12], Support Vector Machine (SVM) method [13], Decision Tree method [14], [15], and K-Nearest Neighbor (KNN) method [6], [16].

From this background description, researchers analyzed sentiment from reviews of the B29 peak tourist attraction in Lumajang using the Backpropagation Neural Network (BNN) classification method. The formulation of the problem carried out in this research is the role of sentiment analysis in analyzing reviews of the Puncak B29 Lumajang tourist attraction based on user comments on Google Maps.

II. Methods

A. Collecting Data

The data obtained in this research are user reviews of the Puncak B29 Lumajang which obtained from Google Maps API. Data collection was carried out by scrapping data using the Outscrapper site. As a result, 500 reviews were obtained with review scores varying from 1 to 5 stars, with details of 3 1-star reviews, 2 2-star reviews, 9 3-star reviews, 74 4-star reviews, and 412 5-star reviews

B. Text Preprocessing

Text preprocessing refers to the transformation of unstructured textual data into structured data. There are four stages in the text preprocessing procedure: case folding, tokenizing, stopwords, and stemming [17].

Case folding is a text preprocessing technique that converts all uppercase characters to lowercase. The case folding process only employs the acceptable characters 'a' through 'z', while all other characters are removed and considered delimiters.. Tokenizing is a text preprocessing

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the process that cuts the input string or sentence based on the words that make it up. Stopwords is a text preprocessing process that takes important words from the tokenization results or deletes words that are too common. Before carrying out stopword removal, there must be a stopword list (stoplist). If it is included in the stoplist, the word is deleted and only the words that characterize the contents of the document are left [18]. Stopword removal can reduce index size and processing time. In this research, the stopword used comes from Sastrawi [19]. Stemming is a text preprocessing process that groups words that have similar base words and meanings but have different meanings because they have different affixes.

C. Word Weighting

After text preprocessing, word weighting is the subsequent stage. This stage assigns a score to the occurrence of words using the Process Document from the Data operator and the method of Term Frequency – Inverse Document Frequency (TF-IDF) [20]. TF is utilized to determine how frequently a word appears in a record [21].

The TF calculation is normalized by dividing it by the duration of the document or by using logarithms to minimize the relative impact of the amount of words that appear frequently in a document. The formula for calculating TF is as follows:

$$tf(t,d) = \begin{cases} 1 + \log(f_{t,d}) & \text{if } f_{t,d} > 0 \\ 0 & \text{if } f_{t,d} = 0 \end{cases} \tag{1}$$

The notation of $tf(t,d)$ is the Term Frequency, and $f_{t,d}$ is the word of word t in record d.

IDF is utilized to determine the significance of a word. When determining TF, all words are considered significant; however, adverbs and words with a high number of occurrences or that appear in nearly all records must be balanced with those that are uncommon (low number of occurrences). The formula for determining IDF is as follows:

$$idf(t,D) = \log\frac{N}{df_t} \tag{2}$$

The notation of N is the total amount of records in a set of records and df_t is the amount of records that contain the word t, if the word value is not present in all records (0), the value is 1.

On the assumption of the TF and IDF calculations given in (1) and (2), the TF-IDF value is computed by multiplying the TF and IDF equations. The formula for determining TF-IDF is as follows:

$$tf.idf(t,d,D) = (1 + \log(f_{t,d}))\left(\log\frac{N}{df_t}\right) \tag{3}$$

The value of TF-IDF can be affected by the frequency with which a term appears in a record, as well as the number of records in the corpus that contain the term. Values can increase proportionally, which helps to compensate for the frequent occurrence of certain terms.

D. Backpropagation Neural Network

BNN is an algorithm for supervised training with multiple layers. BNN utilizes the output defect to modify the value of its weights in reverse. Before this error can occur, the forward propagation phase must be completed [22].

BNN training is comprised of three phases: the forward phase (feed-forward), the backward phase (backpropagation), and the weight modification phase. In the feed-forward phase, the input pattern is determined from the input layer to the output layer in a forward direction. In the backpropagation phase, each output unit receives an error-calculating target pattern that is related to the input pattern. The error will be propagated in reverse. In the meantime, the weight modification stage seeks sites of error. These three phases are repeated until the termination criterion is met [23].

E. Evaluating Classification

In this study, classification testing was conducted by employing the Backpropagation Neural Network (BNN) method, which was then used to ascertain classification performance via a confusion matrix. Accuracy, precision, and recall measurement results are obtained from the confusion matrix. Accuracy is the evaluation of the classification accuracy derived by comparing correctly classified positive and negative data with all data. Precision is an evaluation of the data's relevance to the required information. Recall is an evaluation of the system's ability to retrieve data. Table I displays the confusion matrix [24].

TABLE I. CONFUSION MATRIX

		Actual Class	
		True	***False***
Predicted Class	***True***	TP (*True Positive*)	FP (*False Positive*)
	False	FN (*False Negative*)	TN (*True Negative*)

True Positive (TP) is the condition in which thepredicted data reflects the actual (positive) value. False Positive (FP) refers to a situation in which the predicted data is not as same as the actual value. False Negative (FN) indicates that the

the actual value is greater than the predicted value. True Negative (TN) refers to the situation in which the prognosis is negative and the actual negative is true. In equations 4 to 7, the calculation of accuracy, precision, recall, and F-measure based on the confusion matrix is formulated:

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \tag{4}$$

$$\text{Precision} = \frac{TP}{TP + FN} \tag{5}$$

$$\text{Recall} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{F-Measure} = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{7}$$

III. RESULT AND DISCUSSION

A. Collecting Data Results

Before implementing the method, it is necessary to compile data on Puncak B29 Lumajang reviews obtained via the Google Maps API. Using the Outscrapper website, data was scraped to collect it. The result was 500 reviews with review scores ranging from 1 to 5 stars, including 3 reviews with 1 star, 2 reviews with 2 stars, 9 reviews with 3 stars, 74 reviews with 4 stars, and 412 reviews with 5 stars. In this study, the classification of reviews is divided into two categories: positive sentiment for four- and five-star reviews and negative sentiment for one- to three-star reviews.

B. Text Preprocessing

After data collection, the text preprocessing step is performed, followed by the classification step to analyze review sentiment. The stages of text preprocessing include case folding, tokenization, stopwords, and stemming.

After the steaming process is carried out, the text preprocessing is complete. The next stage is to assign a weight to each word for each dataset, namely by using TF-IDF. Of the 500 reviews on the dataset, 9,214 words have been processed to the stemming stage and there are 2,001 different words if words containing duplicates are removed. TF-IDF weighting begins by looking for TF, which is the number of occurrences of words from each dataset. Details of the calculation are shown in Table II.

TABLE II. CALCULATION OF TF

Data	TF (Peak)	TF(road)	TF(Ojek)	TF(Motorbike)	TF (Pandang)
1	0	0	0	0	0
2	0	0	2	1	0
3	1	0	4	0	0
4	2	0	2	0	2
5	2	0	2	0	2
6	0	1	1	0	0
7	0	1	3	0	0
8	2	0	0	0	0
9	5	4	2	0	0
10	0	0	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
500	1	1	1	1	1

After looking for the TF value of each word for each dataset, the next step is to look for the DF value. The DF value is obtained from the number of occurrences of words in each dataset, whose TF value is more than 0. The DF value is in Table III.

TABLE III. DF VALUE

DF (peak)	DF (road)	DF (ojek)	DF (motorbike)	DF (pandang)
155	151	146	116	145

The next stage, after locating the DF value, is to locate the IDF value for each word in the keyword. By calculating the base 10 log value of the number of records divided by the DF value, the IDF value acts as a counterbalance for words that appear too frequently in all records. When the DF value increases, the IDF value decreases, and vice versa. Based on the derived DF value, the IDF value is as shown in Table IV.

TABLE IV. IDF VALUE

IDF (peak)	IDF (road)	IDF (ojek)	IDF (motorbike)	IDF (pandang)
0,5086	0,5199	0,5346	0,6345	0,5346

After determining the IDF value, the TF-IDF is calculated by multiplying the TF with the IDF. The TF value for the word "puncak" in record number 3 is 2, whereas its IDF value is 0.5086. The TF-IDF value is therefore 2 x 0.5086 = 1,0172. Table 5 shows the results of the TF-IDF calculation.

TABLE V. CALCULATION OF TF-IDF

Data	TF-IDF (peak)	TF-IDF (road)	TF-IDF (ojek)	TF-IDF (motorbike)	TF-IDF (pandang)
1	0	0	0	0	0
2	0	0	1,0692	0,6345	0
3	0,5086	0	2,1384	0	0
4	1,0172	0	1,0692	0	1,0752
5	1,0172	0	1,0692	0	1,0752
6	0	0,5199	0,5346	0	0
7	0	0,5199	1,6038	0	0
8	0,5086	0	0	0	0
9	2,5432	2,0799	1,0692	0	0
10	0	0	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
500	0,5086	0,5199	0,5346	0,6345	0,5376

C. Classification Method Implementation

The number of attributes used in this research is 2,001 attributes containing words after text preprocessing with the value of each attribute based on the TF-IDF calculation that has been obtained. To determine the class, it is determined from the review score from each dataset. If the review score is 1 to 3 stars, it is counted as a "negative" class or 0, while a review score of 4 to 5 stars, is counted as a "positive" class or 1 In this research, there are 14 records that have a negative class and 486 records that have a positive class.

D. Classification Evaluation

This investigation was evaluated using a confusion matrix that included actual and prediction classes. Using formulas 4 to 7, the scores of accuracy, precision, recall, and F1-score are calculated based on the confusion matrix. In this study, various dataset partitioning experiments were conducted, including 60:40 (200 test data), 70:30 (150 test data), and 80:20 (100 test data), within 10, 25, and 50 iterations perspectively. Tables VI to IX display the scores of accuracy, precision, recall, and F1-score for each test set using the Backpropagation Neural Network method.

TABLE VI. ACCURACY RESULT

Number of Test Set	Iteration		
	10	25	*50*
200	7,00%	35,00%	96,00%
150	62,00%	98,67%	99,00%
100	62,50%	97,00%	97,00%
Average	43,83%	76,89%	97,33%

TABLE VII. PRECISION RESULT

Number of Test Set	Iteration		
	10	25	*50*
200	100,00%	83,78%	96,00%
150	100,00%	97,33%	97,98%
100	99,16%	96,98%	96,98%
Average	99,72%	92,70%	96,99%

TABLE VIII. RECALL RESULT

Number of Test Set	Iteration		
	10	25	*50*
200	3,12%	31,63%	100,00%
150	60,95%	100,00%	100,00%
100	61,65%	100,00%	100,00%
Average	41,91%	77,21%	100,00%

TABLE IX. F1-SCORE RESULT

Number of Test Set	Iteration		
	10	25	50
200	6,06%	46,61%	97,98%
150	75,74%	98,64%	98,98%
100	76,03%	98,46%	98,46%
Average	52,61%	81,24%	98,47%

According to Table VI to IX, the sentiment classification based on Puncak B29 reviews on Google Maps using Backpropagation Neural Network has the finest accuracy, recall, and F1-score evaluation results for a total of 50 iterations, with average values of 97.33%, 100%, and 98.43%, respectively. The number of iterations with the highest precision is 10, with an average value of 99.72%. From this description, it can be deduced that the evaluation value will increase in proportion to the number of classification process iterations.

IV. CONCLUSION

Sentiment analysis based on user reviews of Puncak B29 Lumajang is carried out by collecting review data from Google Maps API with a total 500 reviews, with review scores ranging from 1 to 5 stars, including 3 reviews with 1 star, 2

reviews with 2 stars, 9 reviews with 3 stars, 74 reviews with 4 stars, and 412 reviews with 5 stars. Before the sentiment analysis process is carried out, the data that has been collected is processed first through the text preprocessing stage, such as case folding, tokenizing, stopwords, and stemming. After the data is processed, the weight of each word per review is calculated using TF-IDF. After getting the weights with TF-IDF, the data is classified using 3 classification methods, namely Naïve Bayes, Decision Tree, and Backpropagation Neural Network. The dataset that is classified consists of 2,001 attributes in the form of words that have been given TF-IDF weights and the class of the dataset consists of 14 records with the "negative sentiment" class or 0 for reviews with a score of 1 to 3 and 486 records with the "sentiment" class. positive" or 1 for reviews with a score of 4 to 5.

The sentiment analysis classification based on Puncak B29 reviews on Google Maps using Backpropagation Neural Network has the finest accuracy, recall, and F1-score evaluation results for a total of 50 iterations, with average values of 97.33%, 100%, and 98.43%, respectively. The number of iterations with the highest precision is 10, with an average value of 99.72%. From this description, it can be deduced that the evaluation value will increase in proportion to the number of classification process iterations.

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