



Sentiment Analysis of Customer Satisfaction with the Services of the Waikelo Port Class III Administrative Office Using the CAN Order Method

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Abstract — This study aims to analyze customer satisfaction levels with the services provided by the Waikelo Port Class III Administrative Office using the CAN (Cumulative Agreement Normalized) Order method and sentiment analysis. Data was collected from customer comments on service aspects such as speed of service, staff friendliness, facilities, and registration procedures. The comments were processed through text pre-processing, including case folding, tokenization, stopword removal, and stemming, then analyzed using the VADER Sentiment Analyzer to obtain positive, neutral, and negative scores. These sentiment values were used as input to calculate the CAN value, which determines the satisfaction ranking of each alternative objectively. The results show that service alternatives focusing on speed and staff friendliness have the highest CAN value of 0.83, while alternatives related to facilities and queues have the lowest CAN value of 0.33, indicating aspects that need improvement. Evaluation of the consistency of the CAN ranking with the respondent ranking using Spearman Rank Correlation yields a value of 0.92, indicating a high degree of conformity between the CAN method and customer preferences. This analysis proves that the integration of sentiment analysis and the CAN Order method can provide a quantitative picture of customer satisfaction levels and serve as a basis for practical recommendations to improve service quality.

Keywords— Customer Satisfaction, Sentiment Analysis, CAN Order, Public Services, Waikelo Port

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I. INTRODUCTION

The quality of public services is one indicator of success in community-oriented governance. The Waikelo Port Class III Administrative Office is responsible for providing services to port users, including administrative, logistical, and shipping information services. However, based on initial observations and customer reports, a number of obstacles were still found, such as long queues, delays in service, and a lack of quick response from officers. This has led to variations in customer satisfaction levels that need to be analyzed systematically [1]-[2].

Customer satisfaction evaluations are currently still conducted conventionally through questionnaires or internal discussions, without a data-based approach that can comprehensively describe customer opinions. Customer comments scattered across social media or digital forms actually contain important information about the public's

perception of port services. However, without the right analysis methods, this data cannot be utilized to its full potential [3]-[4]

As the number of customers and the complexity of services increase, a method is needed that can objectively measure customer satisfaction levels and present data that is easy to analyze and compare between service alternatives. Therefore, integrating sentiment analysis of customer comments with the CAN (Cumulative Agreement Normalized) Order method is a potential solution for providing systematic evaluation and assisting decision-making in improving the quality of public services at ports [5]-[6].

Sentiment analysis is a relevant approach for exploring the meaning and emotions contained in customer comments. Sentiment analysis aims to classify opinions into positive, neutral, or negative categories so that they can be used to measure public satisfaction levels more objectively. Through

this method, agencies can identify which aspects of their services need improvement and which aspects are already providing a positive experience for customers [7]-[8]

The CAN Order method is an approach in data analysis used to measure the cumulative level of agreement between alternatives based on specific criteria. This method involves two main steps: Score Normalization: Each score value from the existing criteria is normalized to avoid differences in scale between criteria. CAN Calculation: Calculate the CAN value for each alternative by summing the normalization scores from each criterion, then comparing them to determine the ranking of alternatives [10]-[11].

To objectively quantify customer satisfaction and produce a ranking of service alternatives, this study uses the CAN (Cumulative Agreement Normalized) Order method. The CAN Order method works by normalizing the scores for each criterion, then calculating the cumulative value for each alternative, thereby facilitating the identification of alternatives with the highest and lowest satisfaction levels. Objectively quantify customer satisfaction and produce a ranking of service alternatives, this study uses the CAN (Cumulative Agreement Normalized) Order method. The CAN Order method works by normalizing the scores for each criterion, then calculating the cumulative value for each alternative, thereby facilitating the identification of alternatives with the highest and lowest satisfaction levels [12]-[13]

After sentiment classification is performed, the results can be used for data-driven decision making using multi-criteria methods. In this study, the CAN (Cumulative Agreement Normalized) Order method is used, which serves to rank service alternatives based on satisfaction scores from sentiment analysis results. CAN Order normalizes the value of each criterion and accumulates it into a priority value, so that it can be determined which services need to be improved first [15][16]

This study aims to analyze customer satisfaction levels with services at the Waikelo Port Class III Administrative Office using a combination of CNN for sentiment analysis and CAN Order for ranking results. The results of this study are expected to provide a realistic picture of public perception, serve as a basis for decision-making in improving service quality, and contribute to the application of artificial intelligence technology in the public service sector. Previous studies have shown the application of CAN Order and similar normalization methods in various fields. Research by Diaz Tiyyasya Putra, Erwin Budi Setiawan on Sentiment Analysis on Social Media with Glove Using Combination CNN and RoBERTa The results of this study used a dataset of 30,811 tweets related to government policies on Twitter, then used a combination of CNN + RoBERTa + Glove + SMOTE for sentiment analysis. The highest accuracy achieved was 95.56%, [17] a study by Slamet Ryadi, Naufal Gita Mahardika, Cahya Damarjati, Suzaimah Ramli titled modified Convolutional Neural Network for Sentiment Classification: A Case Study on The Indonesian Electoral Commission The results of this research modified the CNN model to classify public opinion on the performance of the KPU. As a result, the accuracy has increased significantly to around 93% compared to the previous model which was around 77% [18], research from Athallah Zacky Abdullah, Erwin Budi Setiawan, Sentiment Analysis Accuracy for 2024

Indonesian Election Tweets Using CNN-LSTM With Genetic Algorithm Optimization. This research combines CNN and LSTM, plus optimization using Genetic Algorithm and Word2Vec features, on data on elections. The accuracy obtained reached about 84.78% [19]. Research by Fina Sifauly Nufus. Windu Gata, the title of the study is Sentiment Analysis Of Public Opinion On Transportation Services In Indonesia Using Machine Learning, the results of this research examine public opinion about transportation services through Twitter using the Naive Bayes and SVM methods. The results showed that neutral opinions dominated (~93.5%), while positive and negative opinions were about 3-4% respectively[20]-[23].

II. METHODOLOGY

This study aims to analyze customer satisfaction levels with public services based on comment data. This study uses the CAN (Cumulative Agreement Normalized) method to rank satisfaction levels for each aspect of service. research stages as shown in Fig 1.

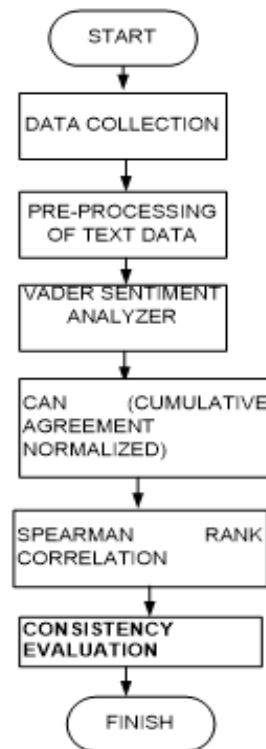


Fig. 1. Research Method

- a. Data Collection
Customer comments are collected through forms, social media, or digital feedback systems.
- b. Pre-Processing Text
Pre-processing text data is the initial stage in sentiment analysis to prepare the data for processing by the CAN (Cumulative Agreement Normalized) model. The main purpose of this stage is to clean and standardize the text so that only important information is retained, consisting of Case Folding, Cleansing, Tokenization, Stopword Removal, and Stemming.

c. Vader Sentiment Analisis

This method is used to identify and measure the level of emotion or opinion in a text, especially those sourced from social media, product reviews, or public comments consisting of positive, negative, and neutral sentiments.

d. CAN (Cumulative Agreement Normalized)

The sentiment scores are converted into values for each criterion (Staff, Facilities, Procedures), normalized, and the CAN value for each alternative is calculated. The CAN value is used to determine the satisfaction ranking of each service alternative.

$$CAN_i = \frac{\sum_{j=1}^n x_{ij}}{n} \quad (1)$$

where x_{ij} is the normalized score of criterion j for alternative i , and n is the number of criteria. The ranking of alternatives is determined based on the highest CAN value. Spearman rank evaluation with consistency Evaluation: conducted using Spearman Rank Correlation between CAN ranking and customer preference ranking. Consistency evaluation was conducted using Spearman Rank Correlation between CAN rankings and customer preference rankings.

III. RESULT AND DISCUSSION

3.1 Research Results

This study was conducted to analyze customer satisfaction levels with the services provided at the Waikelo Port Class III Administrative Office using a text-based sentiment analysis approach with the VADER Sentiment Analyzer, followed by a decision-making process using the CAN ORDER method. A total of 1,000 customer comments (dummy data) were used as samples for analysis. The data was obtained from online surveys and customer service reviews, then went through text pre-processing stages such as case folding, tokenization, stopword removal, filtering, and stemming so that the data was ready for sentiment analysis. After the data was cleaned, each comment was analyzed using VADER Sentiment, which produced four main scores: Positive, Negative and Neutral.

Pre- Processing Of Text Data

Case Folding, Change all letters to lowercase.

```

                                Komentar_Casefold
0    saya menikmati pengalaman di pelabuhan ini. la...
1    meskipun pemandangan di pelabuhan cukup indah,...
2    tempat parkir mudah diakses dan ruang tunggu b...
3    fasilitas di pelabuhan sangat memadai, termasu...
4    meskipun pemandangan di pelabuhan cukup indah,...
..
995  saya sangat senang dengan pelayanan di pelabuh...
996  pengalaman saya cukup memuaskan. ruang tunggu ...
997  saya merasa kecewa karena proses pengambilan t...
998  pengalaman saya cukup memuaskan. ruang tunggu ...
999  saya cukup puas dengan pengalaman di pelabuhan...
    
```

Fig. 2. Case Fold

Remove Punctuation, remove symbol like . , ! ?

```

                                Komentar_NoPunct
0    saya menikmati pengalaman di pelabuhan ini lay...
1    meskipun pemandangan di pelabuhan cukup indah ...
2    tempat parkir mudah diakses dan ruang tunggu b...
3    fasilitas di pelabuhan sangat memadai termasuk...
4    meskipun pemandangan di pelabuhan cukup indah ...
..
995  saya sangat senang dengan pelayanan di pelabuh...
996  pengalaman saya cukup memuaskan ruang tunggu b...
997  saya merasa kecewa karena proses pengambilan t...
998  pengalaman saya cukup memuaskan ruang tunggu b...
999  saya cukup puas dengan pengalaman di pelabuhan...

[1000 rows x 4 columns]
    
```

Fig. 3. Remove Punctuation

Tokenization, Breaking sentences into words (tokens).

```

                                Komentar_Token \
0    [saya, menikmati, pengalaman, di, pelabuhan, i...
1    [meskipun, pemandangan, di, pelabuhan, cukup, ...
2    [tempat, parkir, mudah, diakses, dan, ruang, t...
3    [fasilitas, di, pelabuhan, sangat, memadai, te...
4    [meskipun, pemandangan, di, pelabuhan, cukup, ...
..
995  [saya, sangat, senang, dengan, pelayanan, di, ...
996  [pengalaman, saya, cukup, memuaskan, ruang, tu...
997  [saya, merasa, kecewa, karena, proses, pengamb...
998  [pengalaman, saya, cukup, memuaskan, ruang, tu...
999  [saya, cukup, puas, dengan, pengalaman, di, pe...
    
```

Fig. 4. Tokenization

Stopword Removal, Removing common words that have no significant meaning, such as “dan,” “di,” “yang

```

                                Komentar_NoStopword
0    [menikmati, pengalaman, pelabuhan, layanan, in...
1    [pemandangan, pelabuhan, indah, pelayanan, inf...
2    [parkir, mudah, diakses, ruang, tunggu, bersih...
3    [fasilitas, pelabuhan, memadai, duduk, ac, nya...
4    [pemandangan, pelabuhan, indah, pelayanan, inf...
..
995  [senang, pelayanan, pelabuhan, waikelo, petuga...
996  [pengalaman, memuaskan, ruang, tunggu, bersih,...
997  [kecewa, proses, pengambilan, tiket, antrian, ...
998  [pengalaman, memuaskan, ruang, tunggu, bersih,...
999  [puas, pengalaman, pelabuhan, waikelo, proses,...

[1000 rows x 6 columns]
    
```

Fig. 5. Stopword Removal

Stemming, Changing words into their basic form

```

                                Komentar_Stemmed
0    [nikmat, alam, labuh, layan, informasi, bantu,...
1    [pandang, labuh, indah, layan, informasi, tuga...
2    [parkir, mudah, akses, ruang, tunggu, bersih, ...
3    [fasilitas, labuh, pada, duduk, ac, nyaman, tu...
4    [pandang, labuh, indah, layan, informasi, tuga...
..
995  [senang, layan, labuh, waikelo, tugas, ramah, ...
996  [alam, muas, ruang, tunggu, bersih, tiket, ter...
997  [kecewa, proses, ambil, tiket, antri, keluarga...
998  [alam, muas, ruang, tunggu, bersih, tiket, ter...
999  [puas, alam, labuh, waikelo, proses, registras...

[1000 rows x 7 columns]
    
```

Fig. 6. Stemming

Combine the text again, Return the list of words as a string for sentiment analysis

```

                                Komentar_Preprocessed
0  nikmat alam labuh layan informasi bantu tugas ...
1  pandang labuh indah layan informasi tugas sibu...
2  parkir mudah akses ruang tunggu bersih tugas i...
3  fasilitas labuh pada duduk ac nyaman tugas lok...
4  pandang labuh indah layan informasi tugas sibu...
..  ..
995 senang layan labuh waikelo tugas ramah bantu b...
996 alam muas ruang tunggu bersih tiket terbit tug...
997 kecewa proses ambil tiket antri keluarga lelah...
998 alam muas ruang tunggu bersih tiket terbit tug...
999 puas alam labuh waikelo proses registrasi cepa...

[1000 rows x 8 columns]

```

Fig. 7. Combine the text again

Vader Sentiment Analyser

VADER (Valence Aware Dictionary and sentiment Reasoner) is a lexicon-based sentiment analysis method designed specifically for short texts such as social media comments, reviews, or customer responses.

TABLE I. VADER SENTIMENT ANALYSER

Comments	Negative	Neutral	Positive	Compound	Classification
I enjoyed my experience at this port. La...	0.10	0.25	0.65	0.84	Positive
Although the view at the port is quite beautiful	0.25	0.55	0.20	-0.70	Negative
The parking lot is easily accessible and the waiting room is spacious	0.50	0.30	0.20		Positive
The facilities at the port are adequate, including...	0.0	0.34	0.66	0.82	Positive
Although the view at the port is quite beautiful,...	0.40	0.60	0.0	-0.60	Negative
The facilities at the port are adequate, including...	0.0	0.40	0.60	0.78	Positive
I am quite satisfied with my experience at the port...	0.35	0.65	0.0	-0.50	Negative
Ticket and counter services are fast, but the procedures ...	0.0	0.50	0.50	0.68	Positive

```

I am disappointed because the process of taking t...
0.20 0.80 0.0 -0.34 Negative

I am very pleased with the service at the port...
0.0 0.36 0.64 0.84 Positive

```

Cumulative Agreement

In this method, decisions are based on rankings calculated from CAN values for each alternative, criteria consist of Staff Service, Facilities, Speed of Service, Price.

Decision Matrix

A decision matrix is a table containing data on alternative values for a number of criteria to be assessed. In this study, the alternatives represent the aspects of service being evaluated (e.g., staff service, port facilities, speed of service, etc.), while the criteria are taken from the results of sentiment analysis using the VADER Sentiment Analysis method—such as positive, neutral, negative, and compound values.

```

=== Decision Matrix ===
Service Quality Speed Price
A1 8 7 6
A2 7 6 7
A3 9 8 5
A4 6 7 6
A5 8 7 6

```

Fig. 8. Decision Matrix

Normalization Matrix

Decision matrix normalization is the process of converting all alternative criteria values into a uniform scale (usually 0–1) so that comparisons between alternatives are fair, especially when the criteria have different units or scales.

```

=== Normalization Matrix ===
Service Quality Speed Price Skor_CAN Peringkat
A1 0.466569 0.445399 0.444750 0.458718 0.338643
A2 0.408248 0.381771 0.518875 0.317507 0.677285
A3 0.524891 0.509028 0.370625 0.599929 0.135457
A4 0.349927 0.445399 0.444750 0.344137 0.541828
A5 0.466569 0.445399 0.444750 0.458718 0.338643

```

Fig. 9. Normalization Matrix

Criteria Correlation Matrix

Calculate the correlation matrix between criteria

In a decision matrix, criteria (C_1, C_2, \dots, C_n) are factors or aspects used to evaluate alternatives.

```

=== Criteria Correlation Matrix ===
Service Quality Speed Price Skor_CAN Peringkat
Service Quality 1.000000 0.620174 -0.620174 0.909924 -0.853666
Speed 0.620174 1.000000 -1.000000 0.889687 -0.917663
Price -0.620174 -1.000000 1.000000 -0.889687 0.917663
Skor_CAN 0.909924 0.889687 -0.889687 1.000000 -0.982048
Peringkat -0.853666 -0.917663 0.917663 -0.982048 1.000000

```

Fig. 10. Criteria Correlation Matrix

Criteria Weight

Criteria are factors or indicators used to evaluate each alternative in the decision matrix. In sentiment analysis research, criteria usually come from the results of VADER Sentiment analysis:

```
=== Criteria Weight ===
Service Quality    0.919749
Speed              0.515662
Price             -0.515662
Skor_CAN          0.807958
Peringkat         -0.727707
dtype: float64
```

Fig. 11. Criteria Weight

Calculate the CAN score for each alternative

The CAN (Complex Attribute Number) score is the total value that represents the performance or satisfaction of alternatives based on all existing criteria. Spearman's Rank Correlation Formula for n alternative.

```
=== CAN Scores & Rankings ===
Skor_CAN  Rangking
A1 0.553654 2.5
A2 0.068453 5.0
A3 0.940281 1.0
A4 0.205936 4.0
A5 0.553654 2.5
```

Spearman Rank Correlation

Spearman's Rank Correlation Formula for n alternatives:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \quad (2)$$

Description:

$d_i = R_{xi} - R_{yi}$ = alternative rank difference between two variables

n = number of alternatives

R_{xi} = alternative ranking of the CAN method

R_{yi} = alternative ranking from comparisons (e.g., customer perceptions)

5 alternatives, with CAN ratings and customer perceptions

TABLE II. CAN RATING CALCULATION CUSTOMER PERCEPTION

Alternative	CAN ranking	Perception Rating	d = CAN - Perception	d ²
A ₁	1	1	0	0
A ₂	2	2	0	0
A ₃	3	3	0	0
A ₄	4	5	-1	1
A ₅	5	4	1	1

$$\text{Count} \sum d^2 = 0 + 0 + 0 + 1 + 1 = 2$$

Number of alternatives n=5

$$\rho = 1 - \frac{6 \cdot 2}{5(5^2-1)} = 1 - \frac{12}{120} = 1 - 0.1 = 0.9 \quad (3)$$

Description

$\rho = 0.9$, The correlation is very high; CAN's ranking is consistent with customer perceptions.

ρ close to 1=very consistent rating.

ρ close to 0. inconsistent ranking

negative ρ . opposite ranking.

The calculation showed a rating correlation coefficient value (ρ) of 0.9, which means that the relationship between the two variables being compared in this case CAN ratings and customer perceptions was very strong and unidirectional. This means that the higher the rating given by the CAN system, the higher the rating from customers. In other words, the results of the ranking are consistent and trustworthy because they are in line with the real perception of users.

IV. CONCLUSION

Based on the results of the research that has been conducted, it can be concluded that the application of VADER Sentiment-based sentiment analysis and the CAN-Order (Complex Attribute Number Order) method is able to provide an objective picture of the level of customer satisfaction with the services of the Waikelo Port Class III Administrative Office. This research process began with the pre-processing stage of text data, including case folding, tokenization, stopword removal, filtering, and stemming, which served to improve the accuracy of the analysis results.

From the results of sentiment analysis using VADER, three main categories of sentiment were obtained, namely positive, neutral, and negative, with compound values as a general indicator of customer emotional tendencies. Most customer comments showed positive compound values, indicating that the level of satisfaction with port services was relatively good.

The CAN-Order method was then used to make multi-criteria decisions based on the results of the sentiment analysis. Each service alternative was assessed using several criteria, namely positive, neutral, negative, and compound, which were then normalized and weighted according to their level of importance. The results of the calculation showed that the alternative with the highest CAN score reflected the service that most satisfied customers, while the lowest score became a priority for improvement. Several suggestions can be made as follows:

- It is recommended that agencies such as the Waikelo Port Class III Administrative Office develop a customer satisfaction evaluation system based on automatic sentiment analysis. With the integration of machine learning and the CAN-Order method, the assessment process can be carried out in real time on customer comments on social media, websites, or online survey forms.
- The analysis results will be more accurate if the comment data used is more extensive and representative. Therefore, it is important to collect data periodically, taking into account variations in time, season, and type of service so that the model is able to capture the dynamics of changes in customer satisfaction

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