CLASSIFICATION OF CUSTOMER COMPLAINTS WITH CASE STUDY CONTACT CENTER PLN 123

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***Abstract*— PT PLN (Persero), Indonesia's largest electricity company, focuses on customer service as part of its customer-centric transformation. To enhance customer satisfaction and engagement, PLN offers services via Call Center, PLN Mobile, and social media platforms (Twitter, Instagram, and Facebook). Manual classification of complaints by Contact Center operators into issue types is time-consuming and prone to errors. This study develops a machine learning model to classify customer complaints into issue categories. Using a dataset of complaints from January to December 2023 and the SVM algorithm, the model achieved a 93% accuracy rate, demonstrating its effectiveness in automating complaint classification and improving resource allocation for strategic tasks.**

Keywords: Customer Complaints, Text Classification, Machine Learning, PLN, SVM

I. INTRODUCTION

PT PLN, Indonesia's largest electricity company, has pledged to undergo a customer-focused overhaul aimed at improving its service quality and reputation. This initiative prioritizes the prompt resolution of service issues to elevate customer satisfaction and interaction. As part of this effort, PLN has implemented various customer service platforms, including Call Center PLN Mobile and social media outlets like Twitter, Instagram, and Facebook. All grievances received through these mediums are documented in Contact Center PLN 123, which serves as a communication conduit between PLN and its customers to ensure swift and effective responses to their needs and complaints.

Handling these grievances requires Contact Center operators to manually categorize them into specific types of issues or complaint categories. This manual procedure is time-intensive and susceptible to mistakes, potentially causing delays in resolving customer concerns. The prompt and precise classification is essential for addressing customer complaints in a timely manner, as highlighted in prior research. Thus, there is an urgent requirement for a more effective and accurate approach to classifying complaints.

To tackle this issue, employing text mining methods on unstructured textual data becomes crucial. Text mining involves extracting valuable insights from extensive text collections, automatically recognizing patterns and connections within the text. This is especially beneficial for activities like categorizing texts into predefined groups based on their content, a process known as text classification. Utilizing text mining enables the creation of automated tools that can improve the effectiveness and precision of handling complaints[1].

The goal of this research is to develop a machine learning model that can classify customer complaints into specific issue categories automatically. By examining the text data from customer complaints logged in Contact Center PLN 123 and utilizing advanced machine learning techniques like Support Vector Machine, this study aims to offer PLN a tool for efficiently and precisely categorizing complaints. This, in turn, will assist PLN in strategically allocating resources and enhancing overall performance.

The research focuses on customer complaint data from PLN ULP Campur Darat with media filter in Contact Center PLN 123, covering the period from January 1, 2023, to December 31, 2023. The analysis will involve preprocessing the data to clean and prepare it for modeling, followed by the application of various machine learning techniques to classify the complaints. The primary objective is to evaluate the effectiveness and accuracy of these methods in automatically categorizing customer complaints.

The methodology adopted in this study is the Cross-Industry Standard Process for Data Mining (CRISP-DM), which comprises six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment[2]. This structured approach ensures a thorough and systematic analysis of the data, leading to the development of a robust classification model.

The aim of this study is to demonstrate how efficiently categorizing complaints can enhance PLN's capacity to address customer concerns. Automating the classification process can reduce the time and resources required for manual sorting, minimize errors, and allow a focus on more strategic activities contributing to improved company performance over time..

II. RELATED WORKS

Buntoro [3] conducted research on the 2017 Jakarta Governor Election, focusing on discussions in offline and online platforms, especially Twitter. The study used data preprocessing techniques such as tokenization, cleansing, and filtering, along with Lexicon Based methods for sentiment classification. Naïve Bayes Classifier and Support Vector Machine were utilized for the classification process. The dataset comprised 300 Indonesian tweets containing keywords like AHY, Ahok, and Anies. Results indicated that NBC achieved an average accuracy rate of 95%, precision of 95%, recall of 95%, true positive rate of 96.8%, and true negative rate of 84.6%.

Hermanto et al. [4] researched email complaint processing from students at an academic body (students.bsi.ac.id). The study aimed to identify the best algorithm for classifying student complaints and compare Naïve Bayes with Support Vector Machine. Evaluation methods included Cross-Validation, Confusion Matrix, and ROC Curves. Results showed that the SVM algorithm achieved higher accuracy than Naïve Bayes: 84.45% accuracy rate and AUC value of 0.922 vs. 69.75% accuracy and AUC of 0.679 for Naïve Bayes.

Mustakim and Priyatna [5] conducted an analysis of the KAI Access application from PT. KAI, focusing on aspect-based sentiment analysis due to negative reviews on the Google Play Store. They used Naïve Bayes Classifier and Support Vector Machine with three scenarios: NBC with Multinomial Naïve Bayes, SVM with default Sklearn parameters, and SVM with hyperparameter tuning. The data were collected from Google Play Store reviews. The results showed mostly negative user sentiments across all aspects, particularly regarding the 'errors' aspect due to high system errors. Scenario 3's model performed best, achieving an average accuracy score of 91.63%, an f1-score of 75.55%, precision of 77.60%, and recall of 74.47%.

Silvester et al. [6] aimed to use an automated method to categorize customer feedback and improve customer satisfaction. They proposed using the Naïve Bayes Classifier with R programming to categorize complaints based on the content of customer messages, facilitating management in obtaining statistical data related to customer complaints for decision-making and service improvements.

III. EXPERIMENT AND METHODOLOGY

A. *Problem Analysis*

Based on problem statement the issue to be discussed in this research is the text classification of customer complaints reported through the Contact Center PLN 123 using a machine learning model. Existing research has only used the Naïve Bayes Classifier machine learning model, with results that have not shown how high the accuracy generated by the built machine learning model is[6]. This study aims to use other machine learning models, such as the Support Vector Machine, Random Forest and Logistic Regression, in addition to the Naïve Bayes Classifier, to provide insights into which model performs better in classifying PLN customer complaints.

The dataset used in this study is the text data of customer complaints reported through the Contact Center PLN 123 in 2023. The data comprises complaint texts, complaint categories, and customer information. The dataset will be cleaned, tokenized, and transformed into a matrix representation before being used to train the machine learning models.

B. *Experimental Design*

The methodology used in this research involves the following steps:

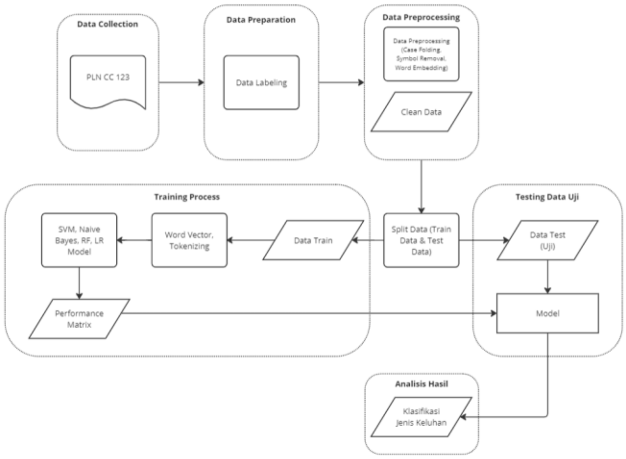

Fig 1. Experimental Design

1) Data Preparation

The collected data will be used for training and testing the model. Before this, the data is labeled by the business process owner (BPO) based on the issue type (complaint category). Following this labeling, Exploratory Data Analysis (EDA) is conducted to understand the distribution of the categorized customer complaints. The distribution is illustrated in Fig 2.

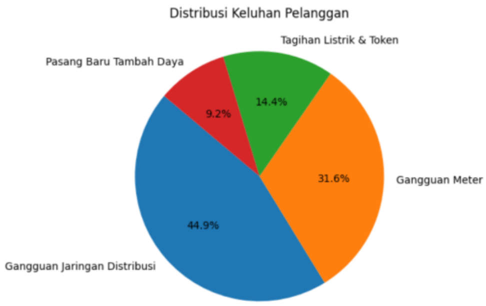

Fig 2 Exploratory Data Analysis

From the figure, it is evident that the most significant issue is the distribution network disruption, as complaints about power outages are the most frequently reported by customers through Contact Center PLN 123. Additionally, the analysis includes identifying the frequently occurring words in the customer complaints before data preprocessing. The word distribution is shown in Fig. 3.

Fig 3 Word Cloud Before Normalization

From the word cloud, it can be observed that dominant words such as "Pelanggan" and "Sisa KWH" appear frequently. These words do not yet show a clear correlation with the categorized customer complaints. Therefore, the next step involves data preprocessing to clean the text data of reported customer complaints.

2) Data Preprocessing

After data preparation, the next step is data preprocessing. Each data entry undergoes data cleaning to optimize the performance of the classification model. The preprocessing steps include case folding, tokenizing, stop words removal, symbol removal, word normalization, and stemming. The preprocessing workflow is illustrated in Fig. 4.

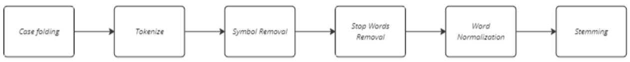

Fig 4 Preprocessing Data

Once the data is cleaned, an analysis of the word distribution reported by customers is conducted.

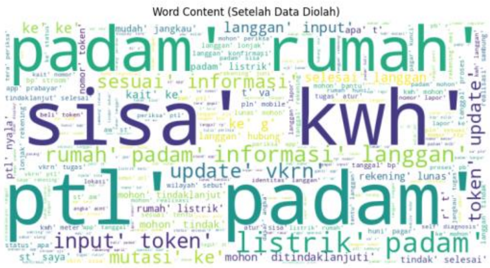

Fig 5 Word Cloud After Normalization

From the word cloud after data preprocessing, it is evident that the most frequently occurring word is "padam," which closely correlates with the "gangguan jaringan distribusi" (distribution network disruption) category. Following exploratory data analysis, the next step is to train the model that will be tested.

3) Training Model

The purpose of the training process is to develop a model using the selected algorithm and evaluate its accuracy in classifying the training data, which will then be applied to test data to assess its performance.

The training model process involves the following steps:

- Data Splitting: The preprocessed data is split into training and testing datasets. The splitting ratio used is 80% for training data and 20% for testing data.
- Feature Extraction: Converting the preprocessed text data into a numerical matrix representation using techniques such as TF-IDF (Term Frequency-Inverse Document Frequency) or Fasttext embeddings[7].
- Model Development: Classification models are developed using four machine learning algorithms: Support Vector Machine (SVM), Multinomial Naïve Bayes, Random Forest, and Logistic Regression.

4) Model Evaluation

After developing the models, their performance is evaluated using performance metrics such as Precision, Recall, F1-Score, and Accuracy.

Comparing the performance of the Support Vector Machine (SVM), Multinomial Naïve Bayes, Random Forest, and Logistic Regression models to determine the most effective approach for classifying PLN customer complaints.

IV. RESULT AND ANALYSIS

A. Experimental Scenario

After the completion of Data Collection and Data Preprocessing and Splitting Data, which led to improved data quality, the next phase involves evaluating the data through machine learning models. The testing in this study involves comparing various methods in Table 1:

Table 1 Experimental Scenario

No	Model	Parameter
1	*SVM*	C:10, gamma=0.1
2	Multinomial *Naïve Bayes*	alpha=1.0, fit_prior=true
3	*Random Forest*	n_estimators=100, random_state=42
4	*Logistic Regression*	max_iter=1000, random_state=42

Following the process of converting data into a numerical format, the accuracy of the models is evaluated using the four specified machine learning techniques. Additionally, further examination of parameters such as recall and precision is carried out to ensure the trustworthiness of the models.

B. Experimental Result

The performance of the four machine learning models was evaluated based on their ability to classify customer complaint categories accurately. The results of this evaluation are summarized in Table 2.

Table 2 Comparison of Model Performance

No	Model	Parameter	Accuracy
1	*SVM*	C:10, gamma=0.1	**93%**
2	Multinomial *Naïve Bayes*	alpha=1.0, fit_prior=true	90%
3	*Random Forest*	n_estimators=100, random_state=42	92%
4	*Logistic Regression*	max_iter=1000, random_state=42	91%

The results presented in Table 1 indicate that the SVM model, with parameters C=10 and gamma=0.1, achieved the highest accuracy at 93%. This demonstrates the SVM model's superior capability in handling the classification of customer complaints into predefined issue categories.

V. CONCLUSION

The SVM model's higher accuracy suggests it is effective in distinguishing between different types of customer complaints by finding the optimal hyperplane that maximizes the margin between classes, indicating superior classification performance and effectiveness in handling complex data structures.

While the Multinomial Naïve Bayes model is simpler and faster, it achieved a slightly lower accuracy of 90%, reflecting its limitation in handling feature dependencies. The Random Forest model performed robustly with 92% accuracy, benefiting from its ensemble learning approach to manage overfitting and capture complex patterns. The Logistic Regression model, with 91% accuracy, serves as an effective baseline classifier, though it may not capture nonlinear relationships as efficiently as SVM or Random Forest.

The high performance of the SVM model can be leveraged by PLN to automate the classification process of customer complaints, thus improving operational efficiency and allowing human resources to focus on more strategic tasks.

Future work could explore the integration of advanced techniques such as deep learning to further enhance classification accuracy. Also testing the capability of multi-label classification models, as customers may report more than one complaint category in a single report. Additionally, analyzing customer complaints reported through social media should be further investigated to provide a more comprehensive understanding of customer issues.

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PERNYATAAN

Dengan ini saya menyatakan bahwa makalah yang saya tulis ini adalah tulisan saya sendiri, bukan saduran, atau terjemahan dari makalah orang lain, dan bukan plagiasi.

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