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BERT-Based Analysis of Indonesian Public Sentiment Toward Pertamina Fuel Purchase Cancellation on Instagram and X

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Abstract — This study analyzes public sentiment toward the cancellation of fuel purchases from Pertamina by private fuel stations using comments collected from Instagram and X (Twitter). Sentiment classification was performed using a fine-tuned Indonesian Bidirectional Encoder Representations from Transformers (BERT) model. The research process included data collection through web scraping, text preprocessing, sentiment labeling into positive, neutral, and negative categories, and model fine-tuning. Experimental results show that the model achieved an accuracy ranging from 85% to 92%, with a macro-average score of 74% and a weighted-average score of 85%, indicating effective performance in sentiment classification. The findings reveal that negative sentiment dominates public discussions regarding the policy, while neutral and positive sentiments appear less frequently. These results demonstrate the potential of BERT-based sentiment analysis for monitoring public opinion on social media and supporting policy evaluation.

Keywords – public opinion, fuel policy, social media, Instagram, BERT

I. INTRODUCTION

Social media's explosive expansion has fundamentally altered how individuals react to public events, laws, and corporate practices as well as how they express their thoughts. Users actively share their opinions through brief posts and comments on Instagram and X (Twitter), two popular sites. Previous research has demonstrated that because social media data is real-time and has a high level of user involvement, it can be a useful source for public sentiment analysis.

According to Pratama et al. (2024), X is a useful tool for sentiment analysis mapping popular opinion on social and public concerns. Meanwhile, there has been a lot of public interest in private fuel stations ceasing to buy petrol from Pertamina. It is strongly linked to the public's susceptibility to changes in fuel prices and problems with energy distribution (Edy Soesanto et al., 2025). These circumstances may affect people's purchasing power and cause public anxiety, especially in areas where daily transit is a major necessity. In this context, sentiment analysis becomes an important approach for extracting and understanding public opinion from large volumes of social media text. One of the most recent and powerful approaches in Natural Language Processing (NLP) is Bidirectional Encoder Representations from Transformers (BERT). BERT is able to capture contextual information bidirectionally, enabling deeper semantic understanding compared to conventional methods.

Therefore, this study aims to analyze public sentiment on Instagram and X regarding the cancellation of fuel purchases from Pertamina by private fuel stations using a BERT-based approach. The results are expected to provide a comprehensive overview of public perception and support policy evaluation related to fuel distribution in Indonesia.

II. METHODOLOGY

A. Research Methodology

This study uses a quantitative descriptive methodology to examine public opinion as it is reflected in social media comments on private gasoline outlets canceling their purchases of Pertamina fuel. Data gathering, text preprocessing, sentiment labeling, model training, testing, and deployment are the primary phases of the overall study framework.

B. Data Collection

X (Twitter) and Instagram were used to gather public comments through web scraping methods that were written in Python. Posts and comments that were publicly accessible were retrieved using predetermined keywords and time ranges, utilizing supporting tools and libraries like BeautifulSoup, Selenium, and accessible unofficial APIs. In order to respect user privacy and ethical considerations, only publicly available data was gathered. The gathered information was saved in CSV files and other structured formats.

C. Text Preprocessing

The collected text data were cleaned to remove URLs, emojis, punctuation, special characters, and other non-textual elements. Case folding was applied to standardize the text, followed by tokenization and stopword removal. The processed text was then prepared according to the input requirements of the BERT model, including tokenization and padding.

D. Data Labeling

Each comment was assigned a sentiment label positive, neutral, or negative based on its semantic meaning. The labeling process was performed manually and semi-automatically to ensure the quality of the annotated dataset.

E. Sentiment Classification Using BERT

A pretrained Indonesian BERT model was employed and fine-tuned using the labeled dataset. The dataset was divided into training, validation, and testing sets. Fine-tuning was conducted by adjusting training parameters such as learning rate, batch size, and number of epochs to obtain optimal performance. The bidirectional contextual capability of BERT enables the model to better capture the semantic meaning of social media text, which often contains informal expressions and ambiguous structures.

F. Model Evaluation

Model performance was evaluated using accuracy, macro recall, and F1-score to measure the classification capability across the three sentiment classes. These metrics were selected to provide a balanced assessment of performance, especially in the presence of class imbalance.

G. System Deployment

The trained model was integrated into a web-based application built using the Flask framework. The system enables administrators to upload new datasets, perform sentiment analysis automatically, and visualize the results through an interactive dashboard. The deployment stage ensures that the proposed approach can be applied in real-world scenarios for continuous monitoring of public sentiment on social media platforms.

III. RESULT DISCUSSION

This section presents the outcomes of the system design, implementation, and testing of the disease prediction framework. The discussion begins with the system architecture design using UML, followed by the interface implementation, functional testing scenarios, and finally the quantitative evaluation of the predictive model's performance.

A. Use Case Diagram

Figure X presents the use case diagram of the proposed sentiment analysis system. The system involves two actors, namely the Admin and the User. The Admin has full access to the system, including logging in, collecting public comments from Instagram and X through the scraping process, performing data preprocessing, and running sentiment analysis using the BERT model. The User is only allowed to log in and view the sentiment analysis results. The main functions of the system consist of login, comment scraping from Instagram and X, data preprocessing, sentiment analysis using BERT, and viewing analysis results. This diagram shows a clear separation of roles, where data processing and analysis are handled by the Admin, while the User only accesses the final results.

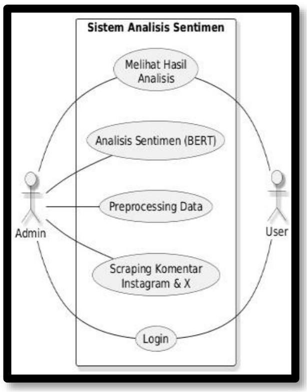

Fig.1. Usecase Diagrama Analysis Model System

B. Implementation Web Aplication Interface

The sentiment analysis results can be accessed by both user roles, namely the admin and the user, through the web application interface. In this menu, users are able to view a summary of the classification results, including the total number of comments categorized as positive, neutral, and negative.

The interface presents the sentiment distribution in a clear and user-friendly format, allowing users to quickly understand the overall public opinion related to the analyzed topic. This feature supports efficient monitoring of sentiment trends and helps users interpret the output of the BERT-based sentiment classification process without requiring technical knowledge of the underlying model.

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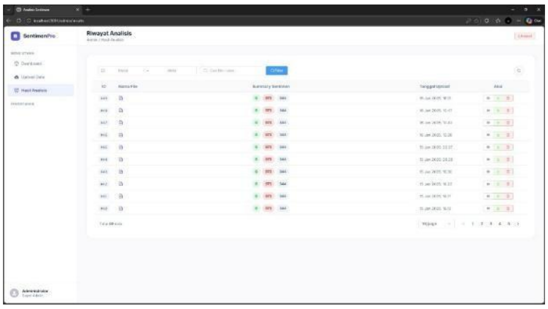

Fig.2. The Result Analysis Sentimen

C. Confusion Matrix

The confusion matrix is a fundamental tool for evaluating the performance of a classification model. It provides a numerical summary of the comparison between the predicted sentiment labels and the actual sentiment labels in the test dataset. The confusion matrix enables the identification of correct and incorrect predictions for each sentiment class. in this study, the confusion matrix is used to describe the following classification outcomes:

1) True Positive (TP) refers to comments that belong to a particular sentiment class and are correctly predicted as that class
2) True Negative (TN) refers to comments that do not belong to a specific sentiment class and are correctly predicted as not belonging to that class.
3) False Positive (FP) refers to comments that do not belong to a specific sentiment class but are incorrectly predicted as that class (for example, a neutral comment predicted as positive).
4) False Negative (FN) refers to comments that belong to a specific sentiment class but are incorrectly predicted as another class (for example, a positive comment predicted as neutral or negative)

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

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1score = 2x \frac{Precision\ x\ Recall}{Precision + Recall}$$

Based on the values obtained from the confusion matrix, several evaluation metrics are calculated to measure the performance of the proposed model. Accuracy represents the proportion of correctly classified samples among all test sample. Precision indicates how accurate the model is when predicting a particular sentiment class. Recall measures the ability of the model to correctly identify all samples that actually belong to a particular sentiment class. F1-score is the harmonic mean of precision and recall, and it provides a balanced measure of classification performance, especially when the dataset is imbalanced across sentiment classes.

D. WordCloud Web Interface

The WordCloud analysis interface presents a visual representation of the most frequently occurring words for each sentiment category, namely positive, negative, and neutral. In this visualization, the size of each word reflects its frequency in the comment dataset, where larger words indicate higher occurrence among social media users.

The word clouds for the negative and neutral sentiments highlight dominant terms that are closely related to public opinions regarding the cancellation of fuel purchases from Pertamina by private fuel stations. Meanwhile, for the positive sentiment category, a notification is displayed when no relevant data are available. This visualization enables users to intuitively identify key terms and contextual patterns that shape public opinion, thereby supporting qualitative interpretation of the sentiment classification results produced by the BERT-based model.

E. Input Output Experiment

The input–output experiment was conducted to demonstrate the operational workflow of the sentiment analysis system in processing comment data and generating sentiment classification results. At the input stage, the system receives public comments collected from Instagram and X, either through direct data acquisition or by uploading dataset files provided by the administrator. The collected comments are subsequently processed through a text preprocessing pipeline and analyzed using a pre-trained and fine-tuned BERT model. The output of this process consists of sentiment labels assigned to each comment, namely positive, negative, or neutral.

Table Head	Testing Input Output		
	Function	Expected Result	Actual Result
1	Trying Login with admin Account	Admin login and land to dashboard page	Admin login and land to the page
2	Trying with wrong password	The system sending a message error	The system sending a error message
3	Registration account	The system sending a message account created	The system seding a account created message
4	Registration with same Username	The system sending a message account has been used	The system sending account has been used message
5	Login with user	The systenm sending welcome user	The system sending user welcome

6	Upload File only support CSV, and XLSX	The system going read the file	The system read the file
7	Upload wrong file neither CSV, and XLSX	The system not respond	System not Respond
8	Renew data & Re-Analysis (Admin)	System updating and re-analysis data	System Updated
9	Logout	Go to Login page	Go to Login page
10	Read Data Analyst	Distribution sentiment graph	Graph distribution

IV. CONCLUSION

This section presents the outcomes of the system design, implementation, and testing of the disease prediction framework. The discussion begins with the system architecture design using UML, followed by the interface implementation, functional testing scenarios, and finally the quantitative evaluation of the predictive model's performance.

The results show that the model is capable of capturing bidirectional contextual information in text and can be effectively applied for social media sentiment analysis. The classification performance is relatively strong for negative sentiment, while the recognition of positive and neutral sentiment remains limited.

The distribution of sentiment indicates that public opinion regarding the analyzed issue is dominated by negative sentiment, reflecting dissatisfaction and rejection toward the policy. The developed system can be used as a supporting tool for monitoring and understanding public opinion in a structured and timely manner.

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