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Sentiment Analysis on Electric Vehicles in Indonesia Using Bidirectional Encoder Representations from Transformers (BERT) and Named Entity Recognition (NER) Methods

Billy[1]*, Wita Oktaviana Br Sinulingga[2], Huliman[3]

[1,2,3]STMIK TIME
billywijaya124@gmail.com[1*], witaoktaviana98@gmail.com[2], dr.huliman@gmail.com[3]

Abstract

Air pollution is a major environmental issue due to its significant impact on human health, with the transportation sector being one of the largest contributors. In Indonesia, increasing motor vehicle usage has led to higher greenhouse gas emissions, encouraging the transition toward electric vehicles as a cleaner alternative. However, the adoption of electric vehicles is influenced not only by technical factors such as infrastructure and cost, but also by public perception, which varies across different digital platforms. This study aims to analyze public sentiment toward electric vehicles in Indonesia using a Natural Language Processing (NLP) approach by combining Bidirectional Encoder Representations from Transformers (BERT) and Named Entity Recognition (NER). BERT is utilized to classify sentiments into positive, negative, and neutral categories by considering bidirectional contextual information, while NER is used to identify key entities such as companies, products, locations, and issues discussed in public discourse. The results show that the BERT model achieves an accuracy of 71.05%, precision of 61.31%, recall of 59.28%, and a misclassification error of 28.95%, indicating a fairly good performance in sentiment classification. Furthermore, NER analysis reveals that event and opinion are the most influential factors affecting public interest, followed by company, product, and quality, while location, price, action, and feature have lower influence. Overall, public interest in electric vehicles in Indonesia is relatively high but dynamic, as it is strongly influenced by circulating information and public opinion.

Keywords: *Sentiment Analysis, Electric Vehicles, BERT; Named Entity Recognition, Natural Language Processing, Indonesia*

1. Introduction

Air pollution is a major environmental issue due to its impact on human health. One of the main contributors to air pollution is the transportation sector, especially land transportation [1]. Based on data from the Climate Transparency Report Indonesia 2022, the transportation sector contributes 25% of greenhouse gas (GHG) emissions in Indonesia. The increasing number of motor vehicles leads to higher emissions of soot from gasoline and diesel, producing more harmful particles that are inhaled and negatively affect both the environment and human health [2]. Concerns over these emissions have significantly increased interest in the electrification of mobility [3]. Electric vehicles are considered one of the solutions to reduce emissions. Battery-powered electric vehicles are regarded as environmentally friendly technology because they produce no emissions during operation [4].

According to information from the Ministry of Industry (Kemenperin), the target for electric car production in Indonesia is 400,000 units by 2025, increasing to 600,000 units by 2030 and 1 million units by 2035. To support this achievement, Kemenperin has proposed an electric vehicle subsidy scheme through VAT incentives (PPN DTP) in 2025 and believes that increasing public purchasing power can help achieve these targets. Electric car sales in Indonesia increased by 60% year-on-year in 2024, reflecting growing public interest in clean energy-based vehicles. In line with this, the government plans to phase out fuel-based vehicles by 2040 and encourage the transition to hybrid or electric vehicles [5].

The main challenge in adopting electric vehicles in Indonesia lies not only in technical aspects such as inadequate charging infrastructure or high vehicle prices, but also in how the public responds to this technology. The emergence of both supportive and opposing views indicates that electric vehicles have not been fully accepted. This is reflected in the varying intensity of public sentiment toward electric vehicles across digital platforms. This phenomenon illustrates a strong dynamic in public opinion, creating what is referred to as intensive sentiment toward electric vehicles in Indonesia, where public perception plays a crucial role in determining the direction and success of the transition to environmentally friendly transportation [6].

To understand public sentiment toward electric vehicles in Indonesia, this study applies a Natural Language Processing (NLP) approach by combining two main methods: Bidirectional Encoder Representations from Transformers (BERT) and Named Entity Recognition (NER). The BERT method is used to classify sentiment from various text sources such as social media, news, and user reviews by considering bidirectional sentence context [7]. Meanwhile, NER is utilized to identify important entities in the text, such as electric vehicle brands, locations, and key issues frequently discussed in public discourse. The combination of these two methods is expected to provide deeper insights into public perception, which can serve as a basis for policy formulation and the development strategy of electric vehicles in Indonesia [8].

In summary, the combination of BERT and NER in this study enables not only the detection of sentiment polarity (positive/negative) by considering bidirectional context, but also the identification of key elements (brands, locations, issues) that become the focus of public opinion, making the analysis more precise and meaningful. For example, the study "The Hybrid of BERT and Deep Learning Models for Indonesian Sentiment Analysis" shows that BERT-based text representation, when combined with deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), improves accuracy compared to a single approach [9].

2. Literature Review

2.1. Sentiment Analysis

Sentiment analysis on social media is the process of evaluating and understanding users' opinions or feelings toward a particular topic through text data generated on a platform. This process aims to identify whether the expressed sentiment is positive, negative, or neutral. With the increasing use of social media, sentiment analysis has become an important tool for businesses and organizations to understand public perception of products, services, or specific issues. This information can be used to inform marketing strategies, improve customer service, and manage brand reputation [10].

2.2. Natural Language Processing (NLP)

Natural Language Processing (NLP) is a field of artificial intelligence (AI) that focuses on understanding and generating human language. Using NLP techniques, computers can process and produce text in a natural way, enabling applications such as machine translation, chatbots, and sentiment analysis [11]. NLP is an important branch of artificial intelligence that deals with the interaction between machines/computers and humans using natural language. One of the main goals of NLP is to extract meaningful insights from unstructured data or content expressed in natural languages, such as English, Bengali, Indonesian, and others. Each language has its own unique structure in terms of grammar, syntax, and conventions. NLP techniques enable computers to read text, understand speech, interpret meaning, measure sentiment or perform opinion mining, and ultimately identify important elements within an intelligent system [12].

2.3. Bidirectional Encoder Representations from Transformers (BERT)

The BERT method is a contextual model designed based on the transformer architecture. Therefore, BERT is capable of capturing and classifying a word within a specific context and level according to the structure of the designed model. BERT represents an important breakthrough in understanding language context by processing text in a bidirectional manner [7]

The selection of an appropriate BERT model to begin the training process is preceded by splitting the dataset into training, validation, and testing sets. After that, the model is fine-tuned according to the requirements. To evaluate the model's performance, metrics such as accuracy and loss are used. For a clearer understanding, see Figure 1, which illustrates the BERT methodology [7]

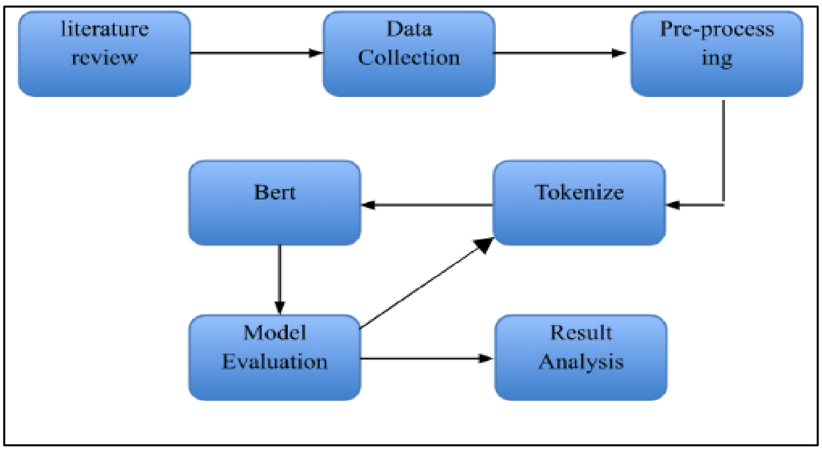

Fig. 1: BERT Working Mechanism

The following explains in detail the basic formula of the BERT method [13]:

$$\text{Attention}(Q, K, V) = \text{Soft max}\left(\frac{Q\,K^T}{\sqrt{d_k}}\right)V \tag{1}$$

Where:
Q is the query matrix,
K^T is the transpose of the key matrix,
d_k is the dimension of the key vector,
Softmax is a function used to normalize the attention scores.

2.4. Named Entity Recognition (BERT)

Named Entity Recognition (NER) is a practical approach for automatically identifying named entities in text and data. NER aims to detect and determine the types of named entities within a text. It can also be used to understand relationships between named entities and in question answering systems. The main task of NER is to locate named entities and classify their types [8].

Currently, NER is widely used, especially in the field of Natural Language Processing (NLP). Initially, NER was developed and used in the Message Understanding Conference (MUC). At that time, MUC focused on information extraction, particularly in extracting information from unstructured data. Therefore, there was a strong need to identify elements within information such as names, places, dates, and times [14].

Overall, the concept of NER serves as a foundation for enhancing the capability of natural language understanding systems and plays an important role in the evolution of automatic information extraction and processing [14].

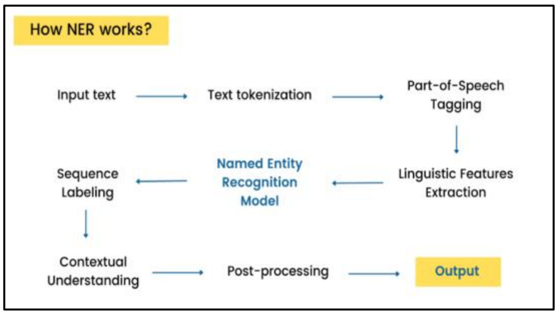

Fig. 2: NER Working Mechanism

3. Research Method

The research method used in this study is illustrated in Figure 3, which presents the flowchart of the research procedures from the initial stage to the final stage.

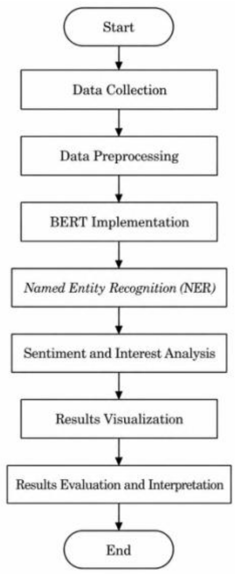

Fig. 3: Flowchart of the Research Method

3.1. Data Collection

At this stage, data is collected from predetermined sources (such as social media, news articles, or public datasets). The data obtained is usually in the form of raw text that still needs to be cleaned and standardized [15].

3.2. Data Preprocessing

The collected text data is then cleaned through processes such as [16]:
1. removing irrelevant characters,
2. text normalization,
3. tokenization,
4. stopword removal,
5. and other necessary processes to prepare the text for BERT processing.

This stage is very important to improve the quality of the model input.

3.3. BERT Implementation

The BERT model is used to process the text and generate more accurate contextual word representations. This stage may include fine-tuning the BERT model according to the analysis requirements.

3.4. Named Entity Recognition (NER)

The BERT model is then applied to detect and extract important entities in the text, such as names of people, organizations, locations, products, or other categories according to the research needs.

3.5. Sentiment and Intereset Analysis

After the entities are obtained, sentiment (positive, negative, neutral) and topic interest or tendencies in the text are analyzed. These results provide an overview of public perception and responses toward the entities.

3.6. Results Visualization

The analysis results are then presented in the form of graphs, charts, or tables to make them easier to understand. Visualization helps in interpreting patterns, trends, and relationships between entities.

3.7. Results Evaluation and Interpretation

This stage involves assessing the accuracy, relevance, and quality of the analysis results. Interpretation is conducted to explain the findings and their implications for the research objectives.

4. Results and Discussion

4.1. Results

The results of this research include the development of a sentiment analysis system regarding electric cars in Indonesia using the Bidirectional Encoder Representations from Transformers (BERT) and Named Entity Recognition (NER) methods. The following is a complete overview of the system's results, including:

1. Login View
   The login screen displays two main input components: username and password fields, and a login button for system access. All elements are centrally arranged for easy viewing and use by users. This screen serves as the initial gateway before users can access the system's features. Figure 4 shows the resulting login screen.

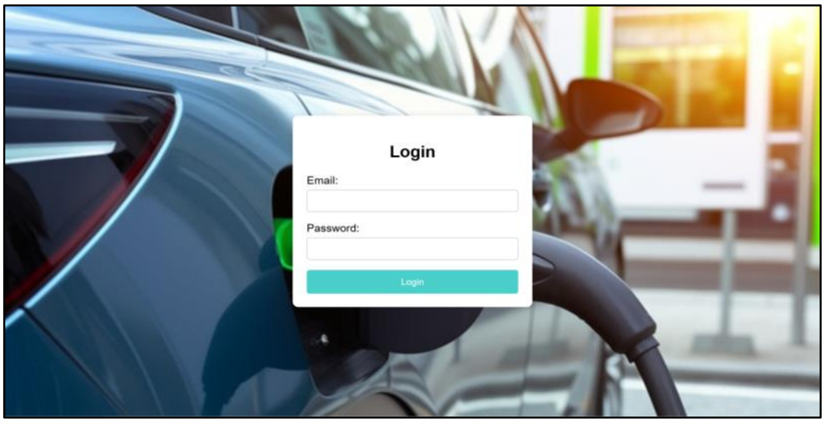

Fig. 4: Login View

2. Manage Dataset View
   The Manage Datasets view contains datasets displayed in tabular form. At the top, there's a button for adding new data. Each row in the table contains dataset information along with action options such as edit and delete. Figure 5 shows the results of the Manage Datasets view.

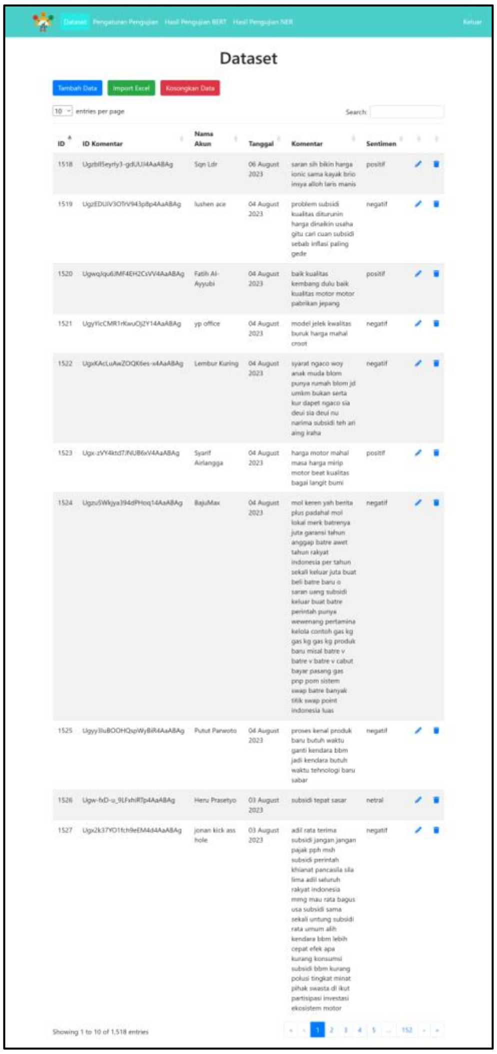

Fig. 5: Manage Dataset View

3. Add Dataset View
   The Add Dataset view provides a form containing columns for entering dataset information, such as comment ID, account name, comment sentiment, and other required attributes. At the bottom, there is a Save button to save the input data and a Back button to return to the previous page. Figure 6 shows the results of the Add Dataset view.

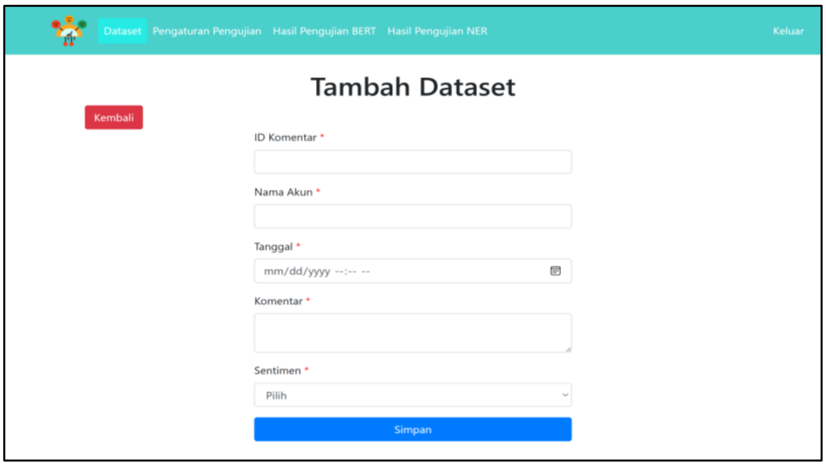

Fig. 6: Add Dataset View

4. BERT Test Results View
   This view presents the results of the BERT model testing in the form of a prediction data table, Confusion Matrix , evaluation metrics (accuracy, precision, recall , and error), as well as a sentiment distribution graph. All information is displayed visually and structured to make it easier for users to understand the mode's performance. Below, Figure 7 shows the results of the BERT test results.

Fig. 7: BERT Test Results View

5. NER Test Results View
   This view displays the NER test results in a table containing each label, along with its frequency and percentage. A bar graph is also displayed to visualize the percentage of each label, allowing users to see the NER label distribution more clearly and informatively. Figure 8 shows a layout of the NER test results view.

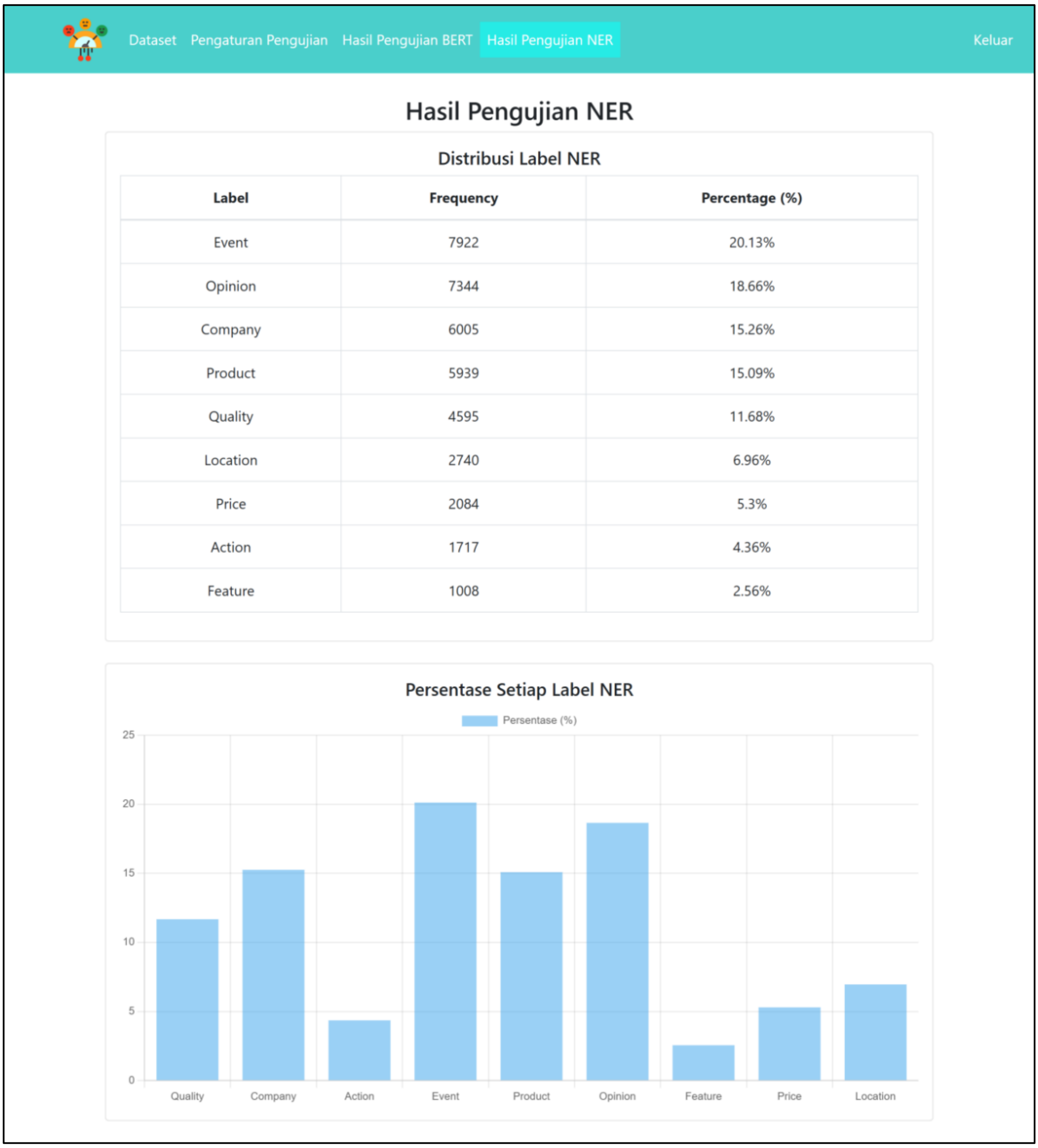

Fig. 8: NER Test Results View

4.2. Discussions

In this discussion subsection, the results of the testing conducted in this study are described, which are divided into two parts: presenting the results of testing the implementation of the BERT method using a Confusion Matrix, and the results of testing the implementation of the NER method in generating entity factors presented in the form of a frequency table of the most frequently occurring factors.

1. Results of Testing the BERT Method Using Confusion Matrix
   The test results are presented in terms of accuracy, precision, recall, and misclassification error from the implementation of the BERT method in analyzing Indonesian public interest in electric vehicles. The BERT method testing was conducted using a Confusion Matrix with a data proportion of 80% training data and 20% testing data. Figure 9 shows the Confusion Matrix from the test results.

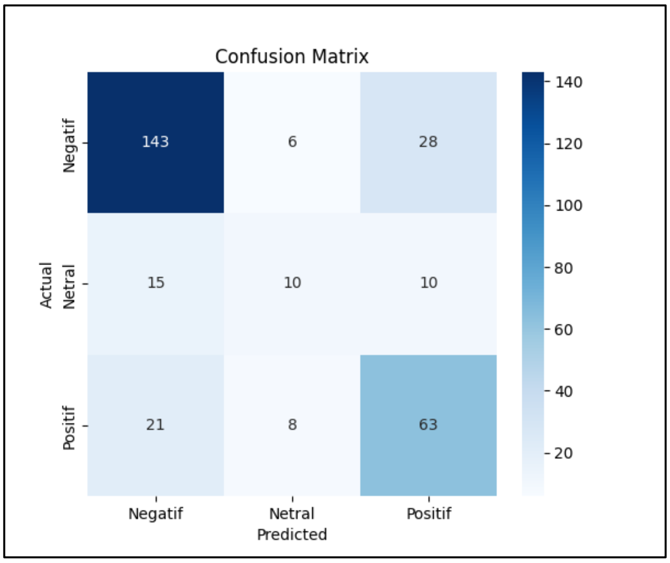

Fig. 9: Results of Testing the BERT Method Using Confusion Matrix

After conducting the Confusion Matrix testing, the values of accuracy, precision, recall, and misclassification error were calculated, as shown in Table 1.

Table 1: Results of Accuracy, Precision, Recall, and Misclassification Error Testing for the BERT Method

Accuracy	Precision	Recall	Misclassification Error
71.05%	61.31%	59.28%	28.95%

Based on Table 1, the test results of the BERT model indicate that its performance in classifying public interest in electric vehicles is fairly good, although it still has some limitations. The accuracy value of 71.05% indicates that the model correctly classifies 71.05% of the total test data. This shows that the model is quite capable of recognizing patterns in the data, although approximately 28.95% of the data is still misclassified, as reflected by the misclassification error value.

Furthermore, the precision value of 61.31% indicates that out of all positive predictions made by the model, only 61.31% are truly correct. This suggests that the model still produces a considerable number of false positives. Meanwhile, the recall value of 59.28% reflects the model's ability to detect actual positive data, meaning it can only identify about 59.28% of all existing positive data. This relatively lower recall indicates that some positive data is not successfully recognized by the model (false negatives).

Overall, the difference between the relatively higher accuracy and the lower precision and recall suggests that the model is better at recognizing general data patterns than accurately classifying each specific class. This may be due to imbalanced data distribution or the limited amount of training data used (80% of the dataset). Therefore, although the model demonstrates fairly good performance, further improvements are needed, such as increasing the amount of training data, parameter tuning, or applying data balancing techniques to achieve more optimal and accurate classification results.

2. Results of Testing the NER Method
The results of testing the implementation of the NER method in generating entity factors are presented in the form of a bar chart showing the frequency of the most frequently occurring factors influencing Indonesian public interest in electric vehicles. Table 4.2 shows the test results.

Table 2: Results of NER Method Testing

Label	**Frequency**	**Percentage (%)**
Event	7,922	20.13%
Opinion	7,344	18.66%
Company	6,005	15.26%
Product	5,939	15.09%
Quality	4,595	11.68%
Location	2,740	6.96%
Price	2,084	5.3%
Action	1,717	4.36%
Feature	1,008	2.56%

Based on Table 2, the results of the Named Entity Recognition method show that various entity factors were successfully identified and classified based on their frequency of occurrence in data related to Indonesian public interest in electric vehicles. Each label represents a type of information or factor frequently discussed by the public in analyzed opinions or conversations.

The Event label has the highest frequency, with 7,922 occurrences (20.13%), indicating that events such as product launches, automotive exhibitions, or government policies are the most dominant factors influencing public interest. The Opinion label ranks second with 7,344 occurrences (18.66%), suggesting that public opinions also play a significant role in shaping perceptions of electric vehicles.

The Company (15.26%) and Product (15.09%) labels indicate that information related to companies and electric vehicle products is also a major concern for the public. This reflects that company reputation and product specifications or types play an important role in attracting interest. Meanwhile, the Quality label (11.68%) shows that aspects such as battery durability or vehicle performance are also frequently discussed.

On the other hand, factors such as Location (6.96%) and Price (5.3%) have lower frequencies but remain relevant in influencing public decisions, particularly regarding infrastructure availability and vehicle affordability. The Action (4.36%) and Feature (2.56%) labels have the lowest frequencies, indicating that actions/activities and additional features are not yet the primary focus in public discussions.

Overall, these results indicate that external factors such as events and public opinion are more dominant than technical factors like features. This suggests that in increasing public interest in electric vehicles, communication strategies should emphasize event-based promotion and the development of positive public opinion.

5. Conclusion

Based on the research findings, the BERT method demonstrates fairly good performance in analyzing public sentiment toward electric vehicles in Indonesia, achieving 71.05% accuracy, 61.31% precision, 59.28% recall, and a 28.95% misclassification error. The NER analysis identifies key factors influencing public interest, with event and opinion being the most dominant, followed by company, product, and quality, while location, price, action, and feature have less influence. Overall, public interest in electric vehicles is relatively high but varies, as sentiment is distributed across positive, neutral, and negative categories and is largely shaped by circulating information and public opinion, making it dynamic and subject to change.

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