ELECTORAL GOVERNANCE
JURNAL TATA KELOLA PEMILU INDONESIA

SENTIMENT ANALYSIS OF DIRECT AND INDIRECT ELECTIONS ON X USING INDOBERT

Raden Adhiyaksa Indiharto[a], Ria Ayu Valleria[b]
[ab]KPU Kabupaten Kepulauan Yapen, Yapen, Indonesia
E-mail: radenadhiyaksa89@gmail.com

ABSTRACT

Social media X (Twitter) has become a digital public sphere where users frequently express political opinions. Discussions concerning direct and indirect local elections often appear through posts and public responses on the platform. These conversations may reflect public attitudes and levels of participation in democratic process. This study aims to examine trends in public sentiment toward direct and indirect election systems using data collected from social media X. This study applies a quantitative approach using web scraping techniques through the tweet-harvest library to collect public tweets. The data were subsequently cleaned and analyzed using the IndoBERT model to understand the context of the Indonesian language and classify user opinions into three sentiment categories: positive, negative, and neutral. The findings indicate that negative sentiment tends to be more dominant, particularly in discussions regarding indirect elections. This suggests that concerns, doubts and resistance toward the issue remain present among parts of the public, although positive sentiment is also evident. Overall, conversations on social media X may provide valuable insights into public perceptions of local electoral systems and political participation in the digital era.

Keywords: sentiment analysis, social media X, direct and indirect elections, political participation, IndoBERT

INTRODUCTION

In simple terms, netizen sentiment refers to how people express their opinions, feelings, or evaluations of an issue on social media. These expressions may take the form of support, criticism, or ordinary informational statements. In research, sentiment is generally classified into three main categories: positive, negative, and neutral.

In academic studies, sentiment on social media is understood as a form of subjective human evaluation toward an object or event expressed through digital text (Nip & Berthelier, 2024, p. 1590). This means that every tweet, comment, or post may contain a certain “emotion” or “attitude” from its user, even when such attitudes are not expressed explicitly. Social media platforms such as X (formerly Twitter) also provide a rich source of data because users can share opinions in real time and with relatively few restrictions. As a result, public sentiment can be observed directly through ongoing digital conversations (Montaser et al., 2025, p. 545).

There are several factors that shape netizen sentiment. First, emotional or personal factors. Many studies show that sentiment is closely related to emotions such as anger, satisfaction, fear, or disappointment. These emotions are often expressed through comments, reactions, or opinions. For example,

harsh criticism frequently emerges from feelings of dissatisfaction or disappointment. In this sense, sentiment can be understood as the result of interactions between emotion, personal experience, and the way individuals interpret information (Nip & Berthelier, 2024, p. 1591).

Second, cognitive factors, including ways of thinking and knowledge. The way individuals understand an issue strongly influences the sentiment they express. People with more complete information tend to provide more structured and argumentative opinions, while those with limited information may respond more reactively or emotionally. Recent studies have therefore used social media sentiment to examine how public perceptions and understandings of issues are formed (Ilyas & Sharifi, 2025, p. 2).

Third, social and environmental factors. Opinions on social media are often influenced by surrounding environments, including friendship networks, online communities, trends, and viral opinions. In other words, individuals may be influenced by dominant opinions circulating on a platform. Research shows that interactions among users and social network dynamics play an important role in the spread and formation of sentiment (Nip & Berthelier, 2024, p. 1592).

Fourth, content-related factors and the issues being discussed. The topic under discussion strongly affects the direction of sentiment. Sensitive issues, such as politics or public policy, tend to generate more negative sentiment or public debate. Many studies show that social media conversations often reveal the dominance of certain sentiments depending on the issue being discussed and how the public perceives it (Wicaksono & Sudarmiatin, 2025, p. 437).

Fifth, the characteristics of social media platforms. Social media has several distinctive characteristics: fast, real-time, brief, and with limited filtering. As a result, opinions expressed on these platforms are often spontaneous, emotional, and sometimes unstructured. Research shows that social media data are complex and unstructured, while also reflecting diverse and dynamic forms of public opinion (Septiani et al., 2024, p. 15).

Political participation reflects the extent to which citizens are involved in political processes and public decision-making, making it one of the main indicators of a democratic system. The level of participation is often used to assess the quality of democracy in a country because higher public involvement can strengthen the legitimacy of policies produced through democratic procedures.

In practice, political participation is not limited to voting. It also includes participation in public discussions, the expression of opinions, and evaluation of existing electoral systems and mechanisms (Artini, 2020, p. 330). In the context of electoral democracy, debates concerning direct and indirect elections remain relevant because they are closely related to government effectiveness, political legitimacy, and the quality of public representation. Public views toward these two electoral systems are therefore important to

examine, as levels of trust and civic engagement are often reflected in the way people assess electoral mechanisms.

In recent years, developments in information technology have expanded political participation into the digital sphere. Social media now functions as a new public space that enables citizens to express opinions openly and quickly. The concept of the digital public sphere explains that interactions on social media may create a relatively open and participatory arena for political discussion (Schäfer, 2016, p. 2). Several studies have also shown that the use of social media is associated with increased political participation, particularly among younger generations (Saud & Ida, 2020, p. 87).

In the Indonesian context, social media also serves as a medium for disseminating political information and shaping public stances toward electoral issues (Herman, 2023, p. 52). Its presence allows citizens to access information quickly and participate in political discussions across space and time. Moreover, the use of X (formerly Twitter) during election periods has been shown to influence forms of political participation, both online and offline (Anwar et al., 2024, p. 319). This indicates that social media functions not only as a communication tool, but also as an interactive space capable of influencing public engagement in democratic processes.

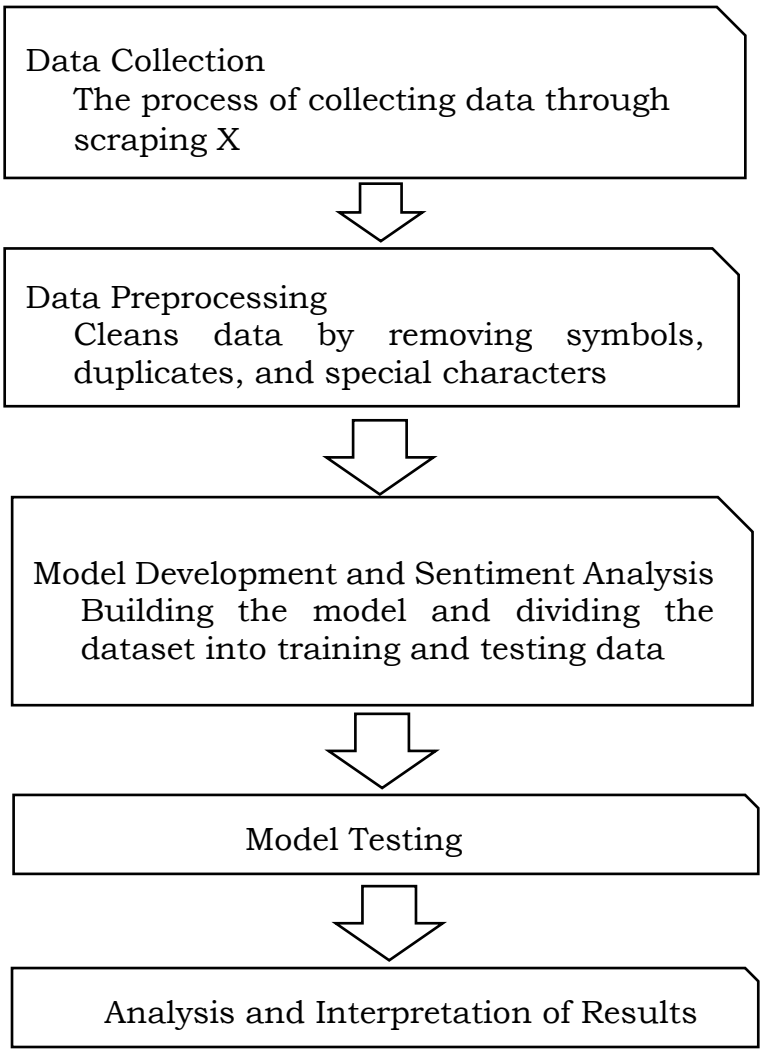
Although research on social media and political participation has developed considerably, studies specifically comparing public sentiment toward direct and indirect elections in Indonesia remain relatively limited. In addition, the integration of sentiment analysis based on modern language models with electoral governance studies has rarely been explored in the context of Indonesian elections. This condition indicates a research gap that may be addressed through social media–based data approaches and more contextual computational analysis.

Based on this background, this study aims to analyze netizen sentiment toward direct and indirect elections using data from social media X (Twitter). The data were collected using the tweet-harvest Node.js library, followed by sentiment analysis using an IndoBERT-based approach. This study is expected to provide a more comprehensive understanding of public perceptions and the dynamics of political participation in the digital era.

RESEARCH METHOD

This study employs a quantitative approach using data collected from the social media platform X (formerly Twitter). The approach is used to identify and measure patterns of public sentiment toward direct and indirect elections based on systematically analyzed textual data. The following stages were applied in this study:

Figure 1.
Research Stages



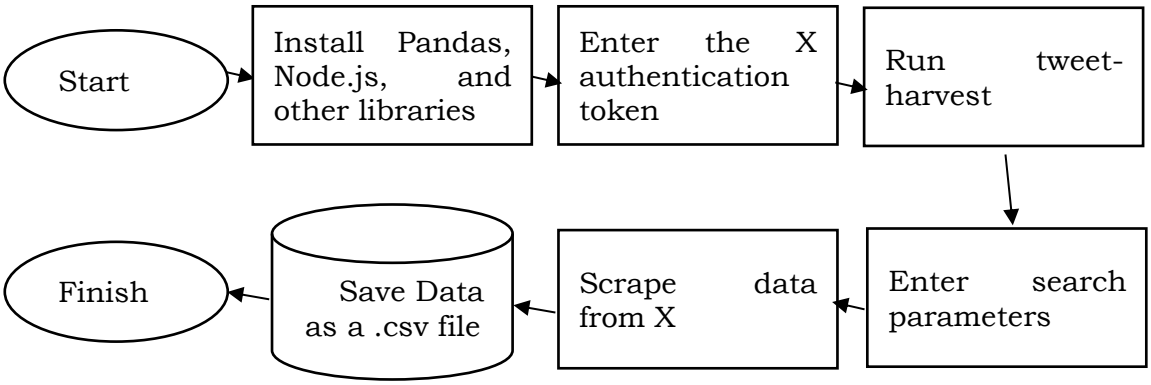
Source: Obtained from primary data sources

The explanation of each research stage is as follows:

1. Data Collection

   The research data consisted of public tweets containing keywords related to direct and indirect elections. Data was collected through a web scraping technique using tweet-harvest, a Node.js library. The collection process was carried out within a specific period to ensure that the data remained relevant to the issues being discussed. This study only used publicly available data and did not include users' personal information. All data was used solely for academic purposes.

Figure 2.
Data Collection Process



Source: Obtained from primary data sources

2. Data Preprocessing
   The data obtained from the scraping process was still in raw form and therefore had to undergo a data-cleaning stage. This stage included removing URLs, unnecessary symbols, excessive punctuation, and duplicate data entries. In addition, text normalization was performed by converting all letters to lowercase and simplifying word forms to ensure consistency across the dataset.
3. Model Building and Sentiment Analysis
   The BERT language model, or Bidirectional Encoder Representations from Transformers, can understand linguistic context more deeply than traditional classification methods (Devlin et al., 2019, p. 1). In this study, sentiment analysis was conducted using IndoBERT, a BERT-based model designed to understand the context of the Indonesian language. This model was selected because it can identify relationships between words in a sentence more contextually than word-frequency-based classification methods. IndoBERT was used to classify each tweet into three sentiment categories: positive, negative, and neutral.

Table 1.
Summary of IndoBERT Fine-Tuning Parameters

Parameters	Value
Model	IndoBERT (fine-tuned, 5 classes)
Learning Rate	2e-5
Batch Size (Train/Eval)	8/8
Epoch (Main)	5 (selected based on loss evaluation)

Source: Obtained from primary data sources

4. Model Testing

To ensure that the classification results had an acceptable level of reliability, a model testing stage was conducted. The testing process involved dividing part of the dataset into testing data and evaluating the classification results using several performance indicators, including accuracy, precision, recall, and F1-score. These indicators were used to assess how well the model classified tweets into the appropriate sentiment categories. Accuracy measures the overall proportion of correctly classified data. Precision indicates the extent to which the model's positive predictions are correct. Recall measures the model's ability to identify all relevant cases within a particular sentiment category. Meanwhile, the F1-score provides a balanced measure between precision and recall, particularly when the distribution of sentiment categories is not fully even. The formulas used to calculate these indicators are as follows:

A. Precision =

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

C. F1-Score $= 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall}$

Notes:
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

This stage aimed to assess how well the model classified textual sentiment and minimize classification errors. The testing results then served as the basis for evaluating the validity of the sentiment analysis conducted in this study.

5. Analysis and Interpretation of Results

After the classification and testing processes were completed, the sentiment results were analyzed to examine the distribution of public opinion toward direct and indirect elections. A comparative analysis was then conducted to identify patterns of sentiment tendency between the two electoral systems. The findings were subsequently interpreted within the broader context of political participation and the dynamics of public discussion in the digital sphere.

RESULTS AND DISCUSSION

Sentiment Analysis

The data used in this study were collected from the social media platform X, which includes tweets containing opinions of users regarding direct and indirect regional head elections. The tweets reflect various public views toward electoral systems that have become part of public discussion in the digital sphere.

Data collection was conducted using the keywords *"pilkada langsung"* (literally, “direct regional head elections”), and the indirect election-related variants *"pilkada tidak langsung," "pilkada tdk langsung,"* and *"pilkada tak langsung."* The data collection period spanned from February 20, 2025, to February 23, 2026. This period was selected to represent one year of leadership following the simultaneous inauguration of regional heads in Indonesia, with the expectation of capturing public opinion dynamics more comprehensively. This stage was aimed to clean and optimize the dataset. The preprocessing stage included text cleansing, text normalization, and tokenization, which refers to the process of separating sentences or paragraphs into individual words. The cleaned dataset for direct elections consisted of 1,012 tweets, while the indirect elections dataset contained 1,353 tweets. The overall dataset comprised 2,365 tweets.

Table 2.
Number of Tweets for Each Keyword

Keywords	Tweet Count
“pilkada langsung”	1,012
“pilkada tidak langsung”	805
“pilkada tdk langsung”	117
“pilkada tak langsung”	431
Total Dataset Size	2,365

Source: Obtained from primary data sources

At the next stage, the study conducted labeling using a zero-shot labeling method. This method refers to a text-classification approach that enables a model to assign categories to data without first being trained on the same dataset. In other words, the model does not require a separate manual labeling process before it can be applied. Such models generally possess language-understanding capabilities acquired through large-scale pretraining. Zero-shot labeling is therefore commonly understood as an approach that utilizes a model’s general knowledge to classify new tasks without additional task-specific training (Puri & Catanzaro, 2019, p. 2).

In this study, zero-shot labeling was used to determine whether a tweet expressed positive, neutral, or negative sentiment. The labels were assigned automatically using the IndoBERT-MNLI model. IndoBERT-MNLI is a BERT-

based language model designed to understand the context of the Indonesian language using a Natural Language Inference (NLI) approach. NLI-based models can assess semantic relationships between a text and a given label, including whether a statement supports, is neutral toward, or contradicts a particular hypothesis (Devlin et al., 2019, p. 2).

The analysis of the direct election topic shows that 416 tweets were classified as positive, 496 tweets as negative, and 100 tweets as neutral. Meanwhile, the indirect election topic generated 733 tweets with negative sentiment, 462 tweets with positive sentiment, and 158 tweets with neutral sentiment. To provide a clearer overview, Table 3 presents a comparison of tweet distribution across positive, neutral, and negative sentiment categories for the topics of direct and indirect elections.

Table 3.
Comparison of Tweet Counts Across Direct and Indirect Election Keywords

Sentiment Type	Direct Election Keywords	Indirect Election Keywords
Positive	416	462
Neutral	100	158
Negative	496	733
Total Tweets	1,012	1,353

Source: Obtained from primary data sources

At the next stage, the model was fine-tuned using the data prepared during the zero-shot labeling phase to classify sentiment into three categories: positive, neutral, and negative. The fine-tuning process was intended to adapt the model to a specific task, in this case sentiment analysis, so that it could better capture the relationship between textual data and sentiment labels and generate more accurate predictions (Hakim et al., 2024, p. 2).

During the training process, the model was trained through several iterations known as epochs. Each epoch indicates that the model has processed the entire training dataset once. In the results presented, the training process was conducted over five epochs. Each epoch produced a training loss value, which indicates the degree of error generated by the model during prediction.

Table 4.
Training Loss per Epoch Across Direct and Indirect Election Keywords

Epoch	Direct Election Keywords	Indirect Election Keywords
1.0	1.1581	1.0667
2.0	0.9938	0.7689
3.0	0.7757	0.4177
4.0	0.4512	0.2053
5.0	0.2290	0.1193

Source: Obtained from primary data sources

During the training process, the training loss of the "direct election" model decreased gradually, from 1.1581 in the first epoch to 0.9938 in the second epoch, 0.7757 in the third epoch, 0.4512 in the fourth epoch, and finally 0.2290 in the fifth epoch. This downward trend indicates that the model became increasingly capable of learning data patterns and generating more accurate predictions throughout the training process.

The fine-tuning results for the indirect election model showed a pattern similar to that of the direct election model. As discussed previously, the training loss value also decreased gradually across epochs. This indicates that the model was able to learn sentiment patterns consistently throughout the training process for both datasets.

Nevertheless, there was a slight difference in the final training loss values. In the indirect election dataset, the training loss in the final epoch reached 0.1193, which was slightly lower than the value obtained for the direct election dataset, namely 0.2290. A lower loss value indicates that the model was better able to fit the data. This difference may have been influenced by the characteristics of each dataset, including the number of tweets, linguistic variation, and the distribution of sentiment across the respective keywords.

The selection of five epochs was based on training results showing that the model continued to improve until the final epoch. Therefore, using five epochs provided the model with a greater opportunity to learn the data more optimally than if the training process had been stopped earlier. The consistent decrease in error values across epochs indicates that the model continued benefiting from the additional training process and achieved better performance in the final epoch.

Overall, the fine-tuning results for both topics indicate that the IndoBERT model was able to learn sentiment patterns effectively. This can be observed from the consistently decreasing error values across all epochs during the training process. These results suggest that the model had reached a sufficient level of stability to be applied in the subsequent sentiment analysis stage for both direct and indirect election topics.

Model Testing

This stage was conducted to measure the model's performance on the validation data using a classification report. Model evaluation was carried out using a confusion matrix and standard evaluation metrics, namely accuracy, precision, recall, and F1-score. In brief, accuracy is calculated by dividing the number of correct predictions by the total number of test data. Precision measures the correctness of predictions for a particular class, while the F1-score represents the harmonic mean of precision and recall (2PR/(P+R)) (Yuswira & Ginting, 2026, p. 1263).

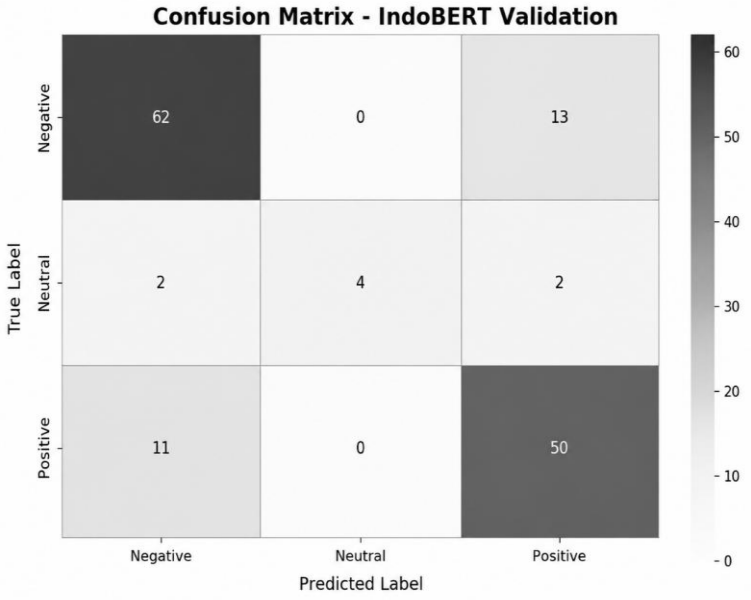
The following calculation is based on the test data for the keyword "pemilihan langsung" (literally, "direct election"), with a total of 144 observations (N = 144): accuracy = (62 + 4 + 50) / 14 4 = 0.81. Table 5 presents the classification report for the direct election test data, while Figure 3.1 shows the confusion matrix of the IndoBERT model for the same dataset.

Table 5.
Classification Report on 'Pemilihan Langsung' Test Data

Sentiment	Precision	Recall	F1-Score	Support
Negative	0.83	0.83	0.83	75
Neutral	1.00	0.50	0.67	8
Positive	0.77	0.82	0.79	61
Macro Average	0.87	0.72	0.76	144
Weighted Average	0.81	0.81	0.80	144

Source: Obtained from primary data sources

Figure 3.
IndoBERT Confusion Matrix (Test Data, N=144)



Source: Obtained from primary data sources

Based on the confusion matrix in Figure 3, the most frequent classification error occurred when neutral tweets were classified as positive, involving two observations. This is understandable because neutral statements on social media platform X often contain implicit contexts such as humor, subtle sarcasm, or simple news quotations that may be interpreted by the model as positive sentiment.

Meanwhile, the classification report indicates that the model performed reasonably well in sentiment classification. Overall, the model achieved an accuracy score of 0.81, or approximately 81%, meaning that most sentiment predictions generated by the model matched the true labels in the validation data.

When examined across individual sentiment categories, the model performance remained relatively stable. In the negative sentiment category, the model achieved identical precision, recall, and F1-score values of 0.83. These results indicate that the model was relatively consistent in identifying and classifying tweets containing negative sentiment. In other words, most negative tweets were successfully identified by the model.

In the positive sentiment category, the model achieved a precision score of 0.77, a recall score of 0.82, and an F1-score of 0.79. The relatively high recall value indicates that the model was able to identify most tweets containing positive sentiment, although several incorrect predictions caused the precision value to be slightly lower.

Meanwhile, in the neutral sentiment category, the model achieved a very high precision score of 1.00, although the recall value was only 0.50, with an F1-score of 0.67. These results indicate that when the model predicted a tweet as neutral, the prediction was almost always correct. However, the model was still unable to identify all tweets that genuinely contained neutral sentiment. This condition may have been influenced by the relatively small amount of neutral data compared with the other sentiment categories.

Overall, the weighted average F1-score of 0.80 indicates that the model performed reasonably well in classifying sentiment within the dataset used in this study. These findings suggest that the fine-tuned IndoBERT model was able to learn sentiment patterns in textual data with a reasonably high level of accuracy, making it suitable for sentiment analysis of social media X data.

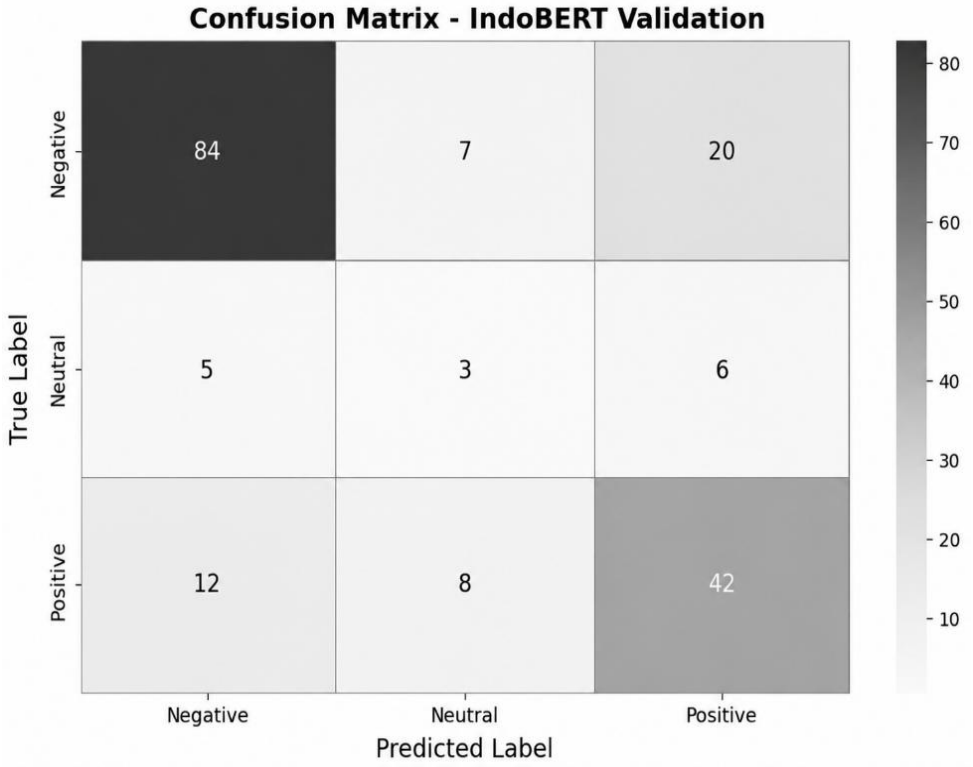
The following analysis is based on the test data for the keywords related to indirect elections, namely "pilkada tidak langsung," "pilkada tdk langsung," and "pilkada tak langsung," with a total of 187 observations ((N = 187)): accuracy = ((84 + 3 + 42)/187 = 0.69). Table 6 presents the classification report for the indirect election test data, while Figure 4 shows the confusion matrix of the IndoBERT model for the same dataset.

Table 6.
Classification Report on Indirect Election Test Data

Sentiment	Precision	Recall	F1-Score	Support
Negative	0.83	0.76	0.79	111
Neutral	0.17	0.21	0.19	14
Positive	0.62	0.68	0.65	62
Macro Average	0.54	0.55	0.54	187
Weighted Average	0.71	0.69	0.70	187

Source: Obtained from primary data sources

Figure 4
IndoBERT Confusion Matrix (Test Data, N=187)



Source: Obtained from primary data sources

The confusion matrix results in Figure 4 show that classification errors occurred most frequently in the neutral class, where six observations were predicted as positive. This phenomenon may be explained by the textual characteristics of platform X, where posts often contain implicit contexts such as humor, irony, or quotations from news reports, which may affect the model's interpretation of the actual sentiment.

The classification report for the indirect election model further shows that the model achieved an accuracy score of 0.69, meaning that approximately 69% of the sentiment predictions generated by the model matched the actual labels in the test data. These results indicate that the model was able to

recognize sentiment patterns in the data with a reasonably good level of accuracy, although several classification errors remained.

When examined across individual sentiment categories, the model's performance varied between classes. In the negative sentiment category, the model achieved a precision score of 0.83, a recall score of 0.76, and an F1-score of 0.79. These values indicate that the model was reasonably effective in identifying tweets containing negative sentiment. Most tweets expressing criticism of or opposition to indirect elections were identified correctly by the model.

In the positive sentiment category, the model achieved a precision score of 0.62, a recall score of 0.68, and an F1-score of 0.65. These values suggest that the model was still able to identify positive tweets reasonably well, although its level of precision was lower than that of the negative category. This condition may have been influenced by the greater linguistic variation found in positive tweets, making them more difficult for the model to learn consistently.

Meanwhile, in the neutral sentiment category, the model performance was relatively low, with a precision score of 0.17, a recall score of 0.21, and an F1-score of 0.19. These values indicate that the model still experienced difficulty in identifying neutral tweets. This condition was likely influenced by the relatively small number of neutral observations compared with the other sentiment categories, limiting the model's ability to learn linguistic patterns associated with this class.

Compared with the evaluation results for direct elections, the indirect election model demonstrated lower overall performance. In the previous analysis of direct elections, the model achieved an accuracy score of approximately 0.81 and a weighted F1-score of approximately 0.80. In addition, the model performance across positive and negative sentiment categories appeared more balanced. By contrast, the indirect election model produced slightly lower accuracy and less even performance across categories, particularly in the neutral sentiment category, which obtained relatively low evaluation scores.

This difference may indicate that linguistic patterns in discussions on indirect elections tend to be more complex or diverse than those found in discussions about direct elections. Variations in how users on social media platform X express their opinions, including the use of sarcasm, irony, or implicit contextual cues, may affect the model's ability to classify sentiment accurately. Nevertheless, overall, the model was still able to capture the primary sentiment patterns in the data with a reasonably good level of performance.

Prediction of the Entire Dataset

This approach used the trained model to assign sentiment labels to 1,012 tweets related to the keyword "pemilihan langsung." Of the total dataset, the model classified 446 tweets as positive sentiment, 522 tweets as negative sentiment, and 44 tweets as neutral sentiment. The complete results are presented in Table 7.

Table 7.
Final Sentiment Label Distribution for Direct Election Tweets

Sentiment Label	Tweet Count
Negative	522
Neutral	44
Positive	446

Source: Obtained from primary data sources

Based on the sentiment distribution, negative sentiment emerged as the most dominant category. This finding indicates that many social media users expressed critical views regarding direct elections. These results are consistent with previous studies showing that social media discussions are often dominated by negative sentiment, particularly in discussions of public policy issues, because users tend to express criticism more actively than support (Manoppo et al., 2025, p. 152).

Nevertheless, the proportion of positive sentiment was also relatively large. This finding suggests that some users still expressed supportive views toward the direct election system. Meanwhile, neutral sentiment appeared less frequently than the other two categories. This condition may be explained by the opinion-oriented nature of social media conversations, where users tend to express clearer positions. Similar findings have also been reported in previous studies, which indicate that sentiment analysis models often experience difficulty in classifying neutral sentiment because of its ambiguous characteristics and its position between positive and negative sentiment (Hakim et al., 2024, p. 2).

Overall, the sentiment distribution regarding direct elections showed a relatively balanced pattern between positive and negative sentiment, although negative sentiment remained slightly more dominant. This pattern reflects the existence of both support and opposition among the public. Previous studies have also shown that sentiment analysis can describe the broader dynamics of public opinion, including identifying sources of public dissatisfaction with political processes (Satriawan et al., 2024, p. 809).

In the analysis of indirect elections, out of a total of 1,353 tweets, the model classified 725 tweets as negative sentiment, 479 tweets as positive sentiment, and 149 tweets as neutral sentiment. This distribution indicates that negative sentiment was more dominant than positive sentiment. These findings suggest that discussions regarding indirect elections tended to

generate greater public concern or opposition. This result is consistent with studies showing that public opinion on social media may be used to evaluate public perceptions of electoral administration and often contains criticism of political institutions and electoral mechanisms (Amirullah et al., 2023, p. 206). The complete results are presented in Table 8.

Table 8.
Final Sentiment Label Distribution for Indirect Election Tweets

Sentiment Label	Tweet Count
Negative	725
Neutral	149
Positive	479

Source: Obtained from primary data sources

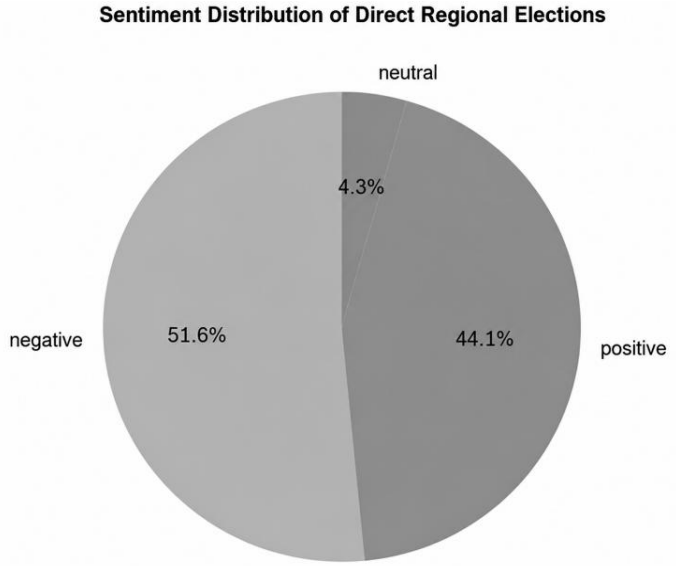
Compared with direct elections, the sentiment distribution regarding indirect elections showed a stronger dominance of negative sentiment. By contrast, sentiment distribution regarding direct elections appeared more balanced. This difference indicates that the two issues generated different public responses on social media. This interpretation is also supported by previous studies explaining that social media conversations reflect diverse forms of public opinion that may shift depending on the issues and contexts being discussed (Yuswira & Ginting, 2026, p. 1259).

Overall, the results of this sentiment analysis indicate that social media may serve as a relevant source of information for examining trends in public views regarding specific political issues. By analyzing conversations emerging on digital platforms, it becomes possible to observe how citizens respond to different discourses concerning electoral mechanisms in a democratic system. These findings further suggest that different electoral mechanisms may generate distinct patterns of public perception in the digital sphere.

Results Interpretation

As part of the results interpretation, data visualization was used to clarify the distribution of sentiment and the words that appeared most frequently in public conversations. The visualization is presented in the form of pie charts for each sentiment dataset, namely direct elections and indirect elections. The following figure presents the sentiment pie chart for direct elections.

Figure 5.
Sentiment Distribution Pie Chart of Keywords Related to Direct Elections



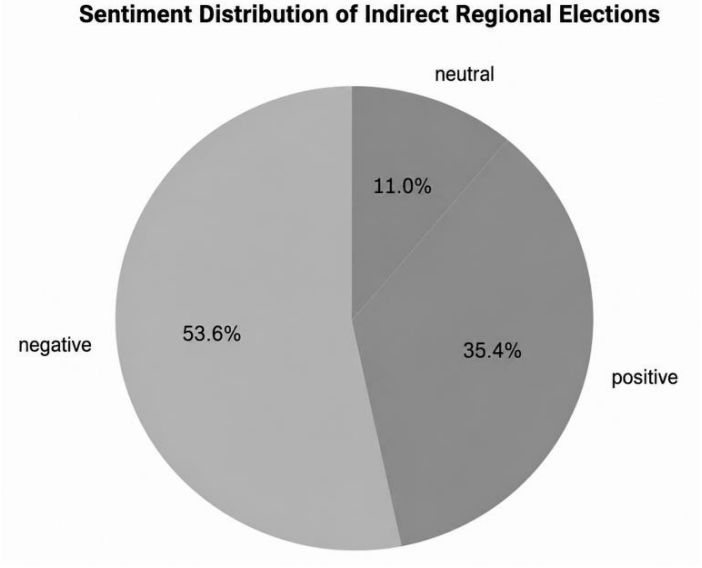
Source: Obtained from primary data sources

Based on the analysis results, negative sentiment was the most dominant category, accounting for approximately 51.6%. These findings indicate that more than half of the tweets discussing the topic expressed critical or skeptical views toward the issue being discussed. On the other hand, positive sentiment also appeared in a relatively large proportion, accounting for approximately 44.1%. This percentage suggests that although many responses were critical in tone, a considerable number of social media users still expressed supportive views or evaluated direct elections positively. The difference between negative and positive sentiment was also relatively small, indicating that discussions on this topic generated diverse public opinions.

Meanwhile, neutral sentiment represented the smallest proportion, at approximately 4.3%. This finding suggests that only a small portion of the conversations was informational in nature or did not clearly indicate either support for or opposition to the issue of direct elections. Overall, the sentiment distribution shown in the chart illustrates that public discussions concerning direct elections on social media tended to be dominated by critical responses, although they were still accompanied by a substantial number of positive opinions. This condition indicates that direct elections remain an issue that generates diverse responses from the public in the digital sphere.

The discussion then shifts to the topic of indirect elections. The sentiment distribution for this topic is presented in the following pie chart.

Figure 6.
Sentiment Distribution Pie Chart of Keywords Related to Indirect Elections



Source: Obtained from primary data sources

The chart illustrates how public opinion regarding indirect elections is distributed across three sentiment categories: negative, positive, and neutral. As shown in the chart, negative sentiment constituted the largest proportion, accounting for approximately 53.6%. This means that more than half of the conversations or opinions expressed disagreement, criticism, or less supportive views toward the indirect election system. This finding may indicate that many people perceived the system as being less aligned with their expectations, for example because it was considered to reduce the public's role in directly electing regional leaders.

Positive sentiment accounted for 35.4%. This figure indicates that a considerable number of people still held favorable views toward indirect elections. They may have perceived advantages in the system, such as greater efficiency, stronger institutional control, or the potential to reduce political conflict within society.

Meanwhile, neutral sentiment represented the smallest proportion, at approximately 11.0%. This category generally consisted of opinions that did not clearly express either support or opposition. Users in this category may simply have shared information, discussed factual matters, or participated in the conversation without taking a clear position.

Overall, the chart indicates that negative views toward indirect elections were more dominant than positive or neutral views. This suggests that, within the analyzed discussions, more users expressed criticism of or disagreement with the system. Based on the analysis and interpretation of the results for both topics, namely direct elections and indirect elections, each topic showed relatively high negative sentiment compared with the positive and neutral sentiment categories. Therefore, the following section presents sample

combined prediction results from both models for each topic, based on test texts selected from observations with prediction accuracy above 90%.

Table 9.
Combined Model Prediction Results for Text Test

Tweet Data	Sentiment Results	Accuracy
"*bagus dah hny presiden, DPR, DPD yg dipilih langsung. Pilkada langsung hny memunculkan raja2 kecil yg sok paling berkuasa sehingga hirarkri dlm birokrasi diabaikan"* ("It's better if only the President, DPR, and DPD are directly elected. Direct regional elections only produce little 'kings' who act overly powerful, disregarding bureaucratic hierarchies.")	NEGATIVE	0.9775
"intinya sama2 busuk. cuman SBY yg berani tolak UU Pilkada tdk langsung dengan nerbitin PERPU si mulyono mana berani emang sengaja cuci tangan aja itu" ("In the end, they're both rotten. Only SBY (i.e., Susilo Bambang Yudhoyono) had the courage to reject the law on indirect regional elections by issuing a PERPU (Government Regulation in Lieu of Law). Mulyono (i.e., Jokowi) wouldn't dare, as he's clearly just washing his hands of the issue.")	NEGATIVE	0.9692
"Rakyat tidak mau dibodohi dan diadu domba dengan Pilkada langsung...kebencian tumbuh subur..." ("People don't want to be deceived and pitted against each other through direct regional elections… hatred keeps growing stronger…")	NEGATIVE	0.9613
"Inilah dampak buruk Pilkada Langsung. Melahirkan pemimpin yang tidak bermutu. Asal populer atau punya dana besar. Maka dipastikan dia akan menang. Walau kualitas gak jelas."	NEGATIVE	0.9589

Tweet Data	Sentiment Results	Accuracy
("This is the negative impact of direct regional elections. They produce low-quality leaders. As long as someone is popular or has lots of money, they're guaranteed to win, even if their actual quality is questionable.")		
"Dua2nya jelek. Pilkada langsung tidak lebih jelek dari pilkada dprd (transaksional siapa mendapat apa siapa mendapat berapa partai dapat apa dan berapa).Sebelum ada yg lebih baik dukung pilkada langsung wakaupyn politisi itu bagi2 uang maling kpd rakyat." ("Both systems are bad. But direct regional elections are still not worse than elections via regional parliament (which are transactional; who gets what, how much each party receives, and so on). Until there's a better system, I'd still support direct regional elections, even if politicians keep distributing stolen money to the people.")	NEGATIVE	0.9528
"Wowo dan koalisi ingin Pilkada tdk langsung adlh langkah awal utk mengamputasi kekuatan Geng Solo. Soalny Mul tanpa kekuatan elektoral benar2 lumpuh. Apalagi PSI jga menolak Pilkada tak langsung" ("Wowo (i.e., Prabowo) and the coalition want indirect regional elections as an initial step to weaken the Solo Gang's power. Without electoral strength, Mul (i.e., Jokowi) would be completely powerless. Even PSI rejects indirect regional elections.")	NEGATIVE	0.9248

Source: Obtained from primary data sources

Based on the combined model prediction results presented in Table 9, most of the analyzed tweets showed a tendency toward negative sentiment regarding the issue of regional head elections. Both direct and indirect election systems became subjects of criticism in public conversations on social media.

This indicates that debates over the mechanisms for electing regional leaders remain sensitive issues and continue to generate diverse public responses.

This negative sentiment did not emerge in a vacuum. Public evaluations of the regional electoral system were also shaped by various experiences in observing political practices in society. Based on the content of the analyzed tweets, several recurring factors appeared to underlie criticism toward both electoral systems.

1. The high cost of administering direct elections

The implementation of direct regional head elections, particularly when conducted simultaneously across multiple regions, requires substantial financial resources. These costs include election logistics, operational expenses for election organizers, the distribution of voting equipment, and security arrangements throughout the electoral process. In addition, candidates are often required to spend considerable amounts of money on campaign activities, program dissemination, and the development of political support networks. This condition has led some members of the public to perceive political competition as increasingly expensive, with not all candidates having equal opportunities to compete.

2. Concerns regarding money politics

High political costs are often associated with the potential for money politics during elections. Some members of the public believe that, in certain situations, voter support may be influenced by the distribution of money or other forms of material assistance. In addition, political campaigns sometimes emphasize candidate popularity more than substantive policy programs. This has generated the perception that leadership quality is not always the primary factor determining electoral outcomes.

3. Concerns regarding the quality of leadership produced

Some public opinions also highlight the possibility that regional elections may produce leaders who lack sufficient leadership capacity. Several tweets reflected the view that electoral victory is not always determined by competence or experience, but may instead be influenced more strongly by popularity or political capital. Such perceptions have contributed to criticism regarding the effectiveness of the electoral system in producing genuinely qualified leaders.

4. Concerns regarding reduced public participation in indirect elections

On the other hand, discourse surrounding indirect regional head elections has also generated public debate. If regional heads are elected by local legislative councils (DPRD), citizens are no longer directly involved in the electoral process. This condition is often perceived as reducing citizens' opportunities for political participation in selecting their regional leaders. For this reason, some members of the public consider the system to have the potential to limit the political rights of citizens.

5. The potential for transactional politics among political elites

Indirect elections are also frequently associated with the possibility of interest-based negotiations among political elites. Electoral processes involving only legislative members may create opportunities for bargaining among political parties or certain political groups. These concerns have led some members of the public to perceive indirect elections as a system that may serve elite interests more than broader public interests.

Overall, the negative sentiment expressed in the analyzed tweets reflects various public concerns regarding regional head election systems. Both direct and indirect elections carry different implications, which in turn generate debate within public discourse. Discussions developing on social media platform X reflect how citizens evaluate various aspects of democratic processes, ranging from political costs and leadership quality to the level of public participation in selecting regional leaders.

CONCLUSION

The results showed that the fine-tuned IndoBERT model was able to categorize sentiment successfully in social media X data. The approach seemed to work more optimally on the topic of direct elections than the topic of indirect elections. The analysis also demonstrated that the netizen sentiment on the topic of the regional head election system tended to be dominated by the negative emotion.

This condition captures the reality of a range of public objections and concerns about the electoral method in question. This feeling is triggered by several things: the high expense of politics, the possibility of money politics, concerns about the quality of leadership and fears about a diminished role for the public in the election process.

This study performs a sentiment analysis, and future studies should follow with a more extensive dataset. In addition, the data sources should be multiplied across social media platforms. This stage is critical to ensure that the representation of public opinion outlets is more inclusive and reflective. In that regard, the results of this study may give a contribution to the policymakers who need to better understand the public sentiment on regional head election systems. The many critiques and concerns that arise in the public domain should be part of policy assessment. Future policy decisions, therefore, are anticipated to prioritize transparency, public participation, as well as the democratic quality of regional processes.

DISCLOSURE STATEMENT

Generative AI tools were used in a limited capacity for language editing, translation refinement, and proofreading assistance. All scholarly interpretation, argumentation, and final manuscript validation remain the responsibility of the author(s).

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