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Sentiment Analysis on the Failure of the Indonesian National Team to the 2026 World Cup During Patrick Kluivert's Coaching Period using the Support Vector Machine (SVM) Algorithm

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Abstract

This study aims to analys public sentiment regarding the failure of the Indonesian National Team to qualify for the 2026 FIFA World Cup during Patrick Kluivert's coaching priod using the Support Vector Machine (SVM) algoritm. Data were collected through web scraping from Twitter (X), YouTube, and Detik.com, resulting in 5,052 comments. The collected data were processed using Natural Language Processing (NLP), including case folding, cleaning, tokenization, stopword removal, normalization, and stemming. The labeled data were transformed using the Term Frequency–Inverse Document Frequency (TF-IDF) method and divided into training and testing sets with an 80:20 ratio. The classification model was developed using a linear kernel SVM and implemented through a Streamlit-based web application for interactive sentiment prediction. The results showed that negative sentiment dominated with 55.0%, followed by positive sentiment at 36.4% and neutral sentiment at 8.6%. Model evaluation achieved an accuracy of 78.44%, precision of 78.54%, recall of 78.44%, and f1-score of 78.48%. These findings indicate that the SVM method is effective in classifying public sentiment toward the performance of the Indonesian National Team.

Keywords: *Indonesian National Team; Natural Language Processing; Sentiment Analysis; Support Vector Machine; TF-IDF*

1. Introduction

Football is one of the most popular sports in Indonesia and has a significant influence on public attention and opinion. The performance of the Indonesian National Team, particularly during the 2026 World Cup qualifiers, has attracted widespread public interest [1]. The appointment of Patrick Kluivert as head coach initially raised high expectations among supporters.

However, the failure of the Indonesian National Team to qualify for the 2026 World Cup has generated diverse reactions from the public. Many individuals express their opinions through digital platforms, ranging from criticism of team strategies and management decisions to support for the players. These responses reflect the emotional and cognitive perspectives of the community toward national football performance.

In the digital era, social media platforms such as Twitter (X), YouTube, and online news portals have become primary channels for expressing public opinion [2]. These platforms provide large-scale textual data that can be analyzed to understand public sentiment in real time. Sentiment analysis enables the classification of opinions into positive, negative, and neutral categories based on textual data.

This study aims to analyze public sentiment toward the failure of the Indonesian National Team in the 2026 World Cup qualifiers using data collected from social media. The Support Vector Machine (SVM) algorithm, combined with a lexicon-based labeling approach, is applied to classify sentiment and evaluate public perception in a structured manner.

2. Research methodology

This study employed the Cross Industry Standard Process for Data Mining (CRISP-DM) framework as a systematic approach to conduct sentiment analysis. CRISP-DM is one of the most widely adopted methodologies in data mining and machine learning projects because it provides a structured process consisting of business understanding, data understanding, data preparation, modeling, evaluation, and

deployment stages [3]. The framework was selected because it offers a comprehensive and iterative workflow for developing data mining solutions, from problem identification to model deployment. The overall research methodology used in this study is illustrated in Figure 1.

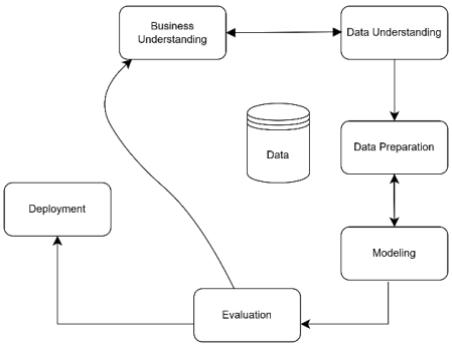

Fig. 1: Research Methodology based on the CRISP-DM framework

2.1. Business understanding

The failure of the Indonesian National Team to qualify for the 2026 FIFA World Cup during Patrick Kluivert's coaching period generated various public reactions across social media platforms. These reactions contain valuable information regarding public perception, criticism, and support toward the team's performance. Therefore, this study aims to analyze public sentiment and classify comments into positive, negative, and neutral categories using the Support Vector Machine (SVM) algorithm.

2.2. Data understanding

At this stage, data were collected from Twitter (X), YouTube, and Detik.com through scraping and crawling techniques. The collected data consisted of comments related to the performance of the Indonesian National Team and Patrick Kluivert during the 2026 FIFA World Cup qualification campaign. A total of 13,274 comments were obtained as raw data. The collected dataset was then examined to understand its characteristics, identify noise, and determine its suitability for sentiment analysis. Social media data are widely utilized in sentiment analysis research because they provide real-time public opinions and reactions [4].

2.3. Data preparation

Data preparation is an important stage in sentiment analysis because textual data collected from social media often contain noise, abbreviations, symbols, and irrelevant information. Several Natural Language Processing (NLP) techniques were applied to improve data quality before classification [5]. The preprocessing stages consisted of:

a. Case Folding
   Converting all characters into lowercase letters to ensure consistency in text representation.
b. Cleaning
   Removing URLs, hashtags, mentions, emojis, punctuation marks, numbers, and other irrelevant characters.
c. Tokenization
   Splitting text into individual words or tokens for further processing.
d. Stopword Removal
   Removing common words that do not contribute significantly to sentiment classification.
e. Word Normalization
   Converting non-standard words, abbreviations, and slang terms into their standard forms.
f. Stemming
   Reducing words to their root forms to eliminate variations of the same word.

After preprocessing, duplicate and irrelevant comments were removed, resulting in 5,052 comments used as the final dataset.

The prepared dataset was subsequently labeled using a lexicon-based approach. Each comment was assigned a positive, negative, or neutral sentiment label based on the sentiment scores obtained from the lexicon dictionary. Furthermore, the labeled comments were transformed into numerical feature vectors using the TF-IDF method. TF-IDF is widely used in text mining because it effectively measures the importance of terms within documents and improves classification performance.

2.4. Modeling

The transformed dataset was divided into training and testing data using an 80:20 ratio. The Support Vector Machine (SVM) algorithm with a linear kernel was employed to classify sentiments into positive, negative, and neutral categories. SVM is recognized as one of the most effective machine learning algorithms for sentiment classification due to its ability to handle high-dimensional text data and produce high classification accuracy [2] [6].

2.5. Evaluation

The performance of the classification model was evaluated using a confusion matrix and classification report. Several evaluation metrics were used, including accuracy, precision, recall, and f1-score. These metrics provide comprehensive information regarding the effectiveness of the model in classifying sentiment categories correctly [7].

2.6. Deployment

The final stage involved implementing the trained model into a Streamlit-based web application. This application allows users to perform sentiment prediction on new comments and visualize sentiment distribution results interactively. Deployment enables machine learning models to be utilized in practical environments and supports decision-making processes based on analytical results [4]

3. Results and discussion

3.1. Data collection results

Data collection was conducted through scraping and crawling techniques on Twitter (X), YouTube, and Detik.com. The collected comments contained public opinions regarding the failure of the Indonesian National Team to qualify for the 2026 FIFA World Cup during Patrick Kluivert's coaching period.
The data collection process successfully gathered a total of 13,274 comments from the three platforms. The collected dataset was subsequently examined to identify duplicate, irrelevant, and noisy data before proceeding to the preprocessing stage.

Table 1: Data Collection Result

Source	Number of Comments
Youtube	8431
Twitter	3557
Detik.com	1286

The collected comments consisted of various forms of public responses, including criticism, support, appreciation, disappointment, and suggestions directed toward the Indonesian National Team and its coaching staff.

3.2. Preprocessing results

The preprocessing stage was performed to improve data quality and prepare the textual data for sentiment classification. Several Natural Language Processing (NLP) techniques were applied, including case folding, cleaning, tokenization, stopword removal, normalization, and stemming.

Table 2: Example of Preprocessing Results

Source	Output
Original Text	SEMANGAT COACH 280 JT RAKYAT INDONESIA MENDUKUNG PERJUANGAN TIMNAS KE PILDUN 2026 SEMOGA KITA TAMPIL BAIK DAN KEBERUNTUNGAN JUGA BERADA DI PIHAK KITA...INSYAH ALLAH...AMIN 👊👊
Case Folding	semangat coach 280 jt rakyat indonesia mendukung perjuangan timnas ke pildun 2026 semoga kita tampil baik dan keberuntungan juga berada di pihak kita.... insyah allah... amin 👊👊
Cleaning Data	semangat coach jt rakyat indonesia mendukung perjuangan timnas ke pildun semoga kita tampil baik dan keberuntungan juga berada di pihak kita insyah allah amin
Tokenizing	semangat, coach, jt, rakyat, indonesia, mendukung perjuangan, timnas, ke, pildun, semoga, kita, tampil, baik, dan, keberuntungan, juga, berada, di, pihak, kita, insyah, allah, amin
Stopword Removal	semangat, coach, rakyat, indonesia, dukung, juang, timnas, piala, dunia, moga, tampil, untung, insyah, allah, amin
Word Normalization	semangat, coach, rakyat, indonesia, mendukung, perjuangan, timnas, piala, dunia, semoga, tampil, keberuntungan, insyah, allah, amin
Stemming	semangat, coach, rakyat, indonesia, dukung, juang, timnas, piala, dunia, moga, tampil, untung, insyah, allah, amin

The preprocessing process successfully removed duplicate and irrelevant data, reducing the dataset from 13,274 comments to 5,052 comments. These comments were subsequently used for sentiment labeling and classification.

3.3. Sentiment labeling results

The preprocessed comments were labeled using a lexicon-based approach. Each comment was assigned a positive, negative, or neutral sentiment label based on sentiment scores obtained from the sentiment lexicon dictionary.

Table 3. Sentiment Distribution

Sentiment	Total Comments	Percentage
Positive	2.780	55,0%
Negative	1.837	36,4%
Neutral	435	8,6%
Total	5.052	100%

Based on the sentiment distribution results, negative sentiment dominated the dataset. This indicates that most public responses expressed disappointment and criticism regarding the Indonesian National Team's failure to qualify for the 2026 FIFA World Cup. Meanwhile, positive comments generally contained support and appreciation for the team and coaching staff, while neutral comments mainly consisted of informational and non-opinionated statements.

3.4. TF-IDF feature extraction results

After sentiment labeling, the comments were transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) method. TF-IDF was employed to calculate the importance of terms appearing within the dataset.

Table 4. Sample TF-IDF Weights

Term	TF-IDF Weight
semangat	1,0772938
coach	1,0772938
rakyat	1,0772938
indonesia	0,8229882
dukung	1,0772938
juang	1,0772938
timnas	0,7290985
piala	0,8651918
dunia	0,8651918
moga	1,0772938
tampil	1,0772938
untung	1,0772938
insyah	1,0772938
allah	0,9834372
amin	1,0772938

The TF-IDF process enabled textual data to be converted into feature vectors that could be processed by the Support Vector Machine classifier. Terms that appeared frequently in specific documents while remaining uncommon across the dataset received higher weights and contributed more significantly to sentiment classification.

3.5. Classification results

The transformed dataset was divided into training and testing sets using an 80:20 ratio

Table 5. Data Splitting Results

Dataset	Total Data
Training data	4,041
Testing data	1,011
Total	5,052

The training dataset was used to build the Support Vector Machine classification model, while the testing dataset was used to evaluate the model's performance on unseen data. The classification process successfully categorized comments into positive, negative, and neutral sentiment classes.

3.6. Evaluation results

The performance of the Support Vector Machine model was evaluated using a confusion matrix and classification report. Evaluation metrics included accuracy, precision, recall, and f1-score.

a. Confusion matrix

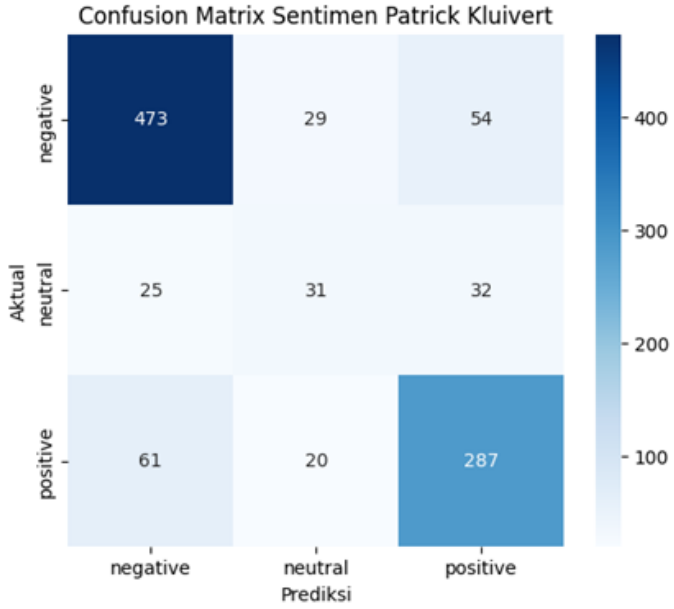

Fig. 2: Confusion Matrix of Sentiment Classification

The confusion matrix results indicate that the model was able to classify most sentiment categories correctly. For the negative sentiment class, 473 comments were correctly classified as negative, while 29 comments were misclassified as neutral and 54 comments as positive. For the neutral sentiment class, 31 comments were correctly identified, while 25 comments were classified as negative and 32 comments as positive. Meanwhile, for the positive sentiment class, 287 comments were correctly classified, with 61 comments misclassified as negative and 20 comments as neutral.

b. Classification report

To provide a clearer evaluation of model performance, the classification report is presented in Fig. 3:

```
Akurasi: 0.7843719090009891

Laporan Klasifikasi:
              precision    recall  f1-score   support

    negative       0.85      0.86      0.85       556
     neutral       0.33      0.34      0.34        87
    positive       0.80      0.77      0.79       368

    accuracy                           0.78      1011
   macro avg       0.66      0.66      0.66      1011
weighted avg       0.79      0.78      0.78      1011
```

Fig. 3: Classification Report

The experimental results show that the Support Vector Machine model achieved an overall accuracy of 78.44%, indicating that the model was capable of classifying sentiments effectively. The negative sentiment class achieved the highest performance, with a precision of 0.84, recall of 0.85, and f1-score of 0.85. This result suggests that the model was highly effective in identifying negative comments related to the Indonesian National Team's performance during Patrick Kluivert's coaching period.

The positive sentiment class also demonstrated good performance, achieving a precision of 0.79, recall of 0.77, and f1-score of 0.78. These results indicate that the model was able to recognize supportive and appreciative comments with relatively high accuracy.

In contrast, the neutral sentiment class obtained the lowest performance, with a precision of 0.33, recall of 0.34, and f1-score of 0.33. This lower performance may be attributed to the ambiguity of neutral comments, which often contain contextual information that overlaps with both positive and negative sentiments. As a result, the model experienced greater difficulty in distinguishing neutral comments from other sentiment categories.

Overall, the findings demonstrate that the combination of TF-IDF feature extraction and the Support Vector Machine algorithm is effective for sentiment classification tasks involving social media comments. The model achieved satisfactory performance, particularly in identifying dominant negative and positive sentiments expressed by the public regarding the Indonesian National Team's failure to qualify for the 2026 FIFA World Cup.

3.7. Deployment results

The final classification model was implemented in a Streamlit-based web application to facilitate sentiment prediction and result visualization.

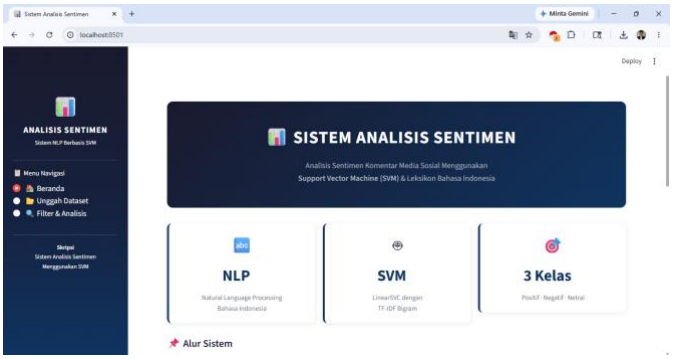

Fig. 4: Main Interface of the Streamlit Application

The developed Streamlit application provides several features to support sentiment analysis, including dataset upload, sentiment visualization, word cloud generation, SVM classification results, classification reports, confusion matrix visualization, and sentiment prediction. These features enable users to interactively analyze sentiment data and evaluate model performance.

After preprocessing, the system will display a sentiment visualization. In fig. 5: there are labeling results using a lexicon-based dictionary. A total of 5,052 data was obtained, 1,837 data labeled positive, 2,780 data labeled negative, and 435 data labeled neutral.

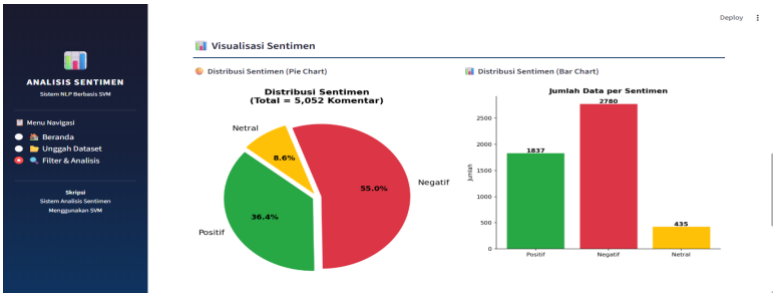

Fig. 5: Labeling Results

In addition to sentiment visualization, in Fig. 6 and Fig. 7 there are also wordcloud of all comments, wordcloud positive, wordcloud negative, and neutral wordcloud

Fig. 6: Wordcloud all comments

Fig. 7: Wordcloud Positive, Negative and Neutral

In fig. 8 there is a comment prediction feature that uses the comment "patrick failed to bring indonesia to the world cup" and the output is negative, with a positive accuracy of 10.5%, negative accuracy of 81.1% and neutral accuracy of 8.3%

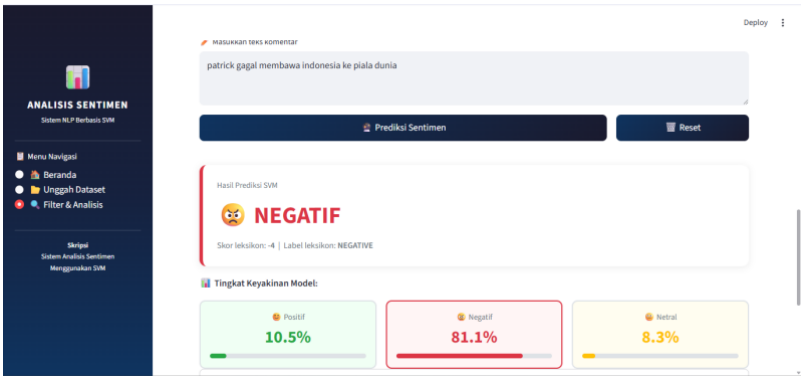

Fig. 8: Comment Prediction Feature

4. Conclusion

This study successfully applied the Support Vector Machine (SVM) algorithm to classify public sentiment regarding the performance of the Indonesian National Team during Patrick Kluivert's coaching period. Using the CRISP-DM framework, a total of 13,274 comments were collected from Twitter (X), YouTube, and Detik.com. After the preprocessing stage, 5,052 comments were retained and transformed into numerical features using the TF-IDF method.

The experimental results showed that the proposed model achieved an accuracy of 78.44%. The negative sentiment class obtained the highest classification performance with a precision of 0.84, recall of 0.85, and F1-score of 0.85, while the positive sentiment class achieved a precision of 0.79, recall of 0.77, and F1-score of 0.78. The lower performance of the neutral class indicates that distinguishing neutral sentiments remains a challenge due to their contextual similarity with positive and negative sentiments.

Furthermore, the developed model was successfully implemented in a Streamlit-based web application that supports sentiment visualization, classification reporting, confusion matrix analysis, and sentiment prediction. These findings demonstrate that the combination of TF-IDF and SVM provides effective performance for sentiment classification on social media data related to public responses toward national football events.

Future studies may compare SVM with other machine learning or deep learning approaches and utilize larger datasets to further improve classification performance.

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