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PUBLIC SENTIMENT ANALYSIS OF THE INDONESIAN NATIONAL FOOTBALL TEAM ON INSTAGRAM USING NAIVE BAYES

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ABSTRACT

Social media platforms such as Instagram have become essential spaces for fans of the Indonesian National Football Team to articulate their reactions and support. Systematically analyzing these comments offers a valuable window into the collective sentiment and perception surrounding match outcomes and team management decisions. This research applies the Naive Bayes Classifier (NBC), a widely recognized probabilistic method for text classification, to categorize Instagram comments into sentiment classes. The NBC operates on the principle of conditional probability and is particularly advantageous due to its efficiency with limited training data. Between September 5, 2024, and March 25, 2025, a dataset of 1,500 comments was assembled from 15 Instagram posts reflecting different match results—victories, draws, and defeats. The analysis revealed that while NBC attained an overall classification accuracy of 90%, its performance varied across sentiment categories. The model was especially adept at identifying Neutral comments, achieving high precision and recall, but demonstrated limitations in reliably classifying Positive and Negative sentiments. These findings highlight both the potential and the challenges of deploying NBC for sentiment analysis in imbalanced social media datasets.

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1. INTRODUCTION

Sport plays a vital role in human life and contributes to enhancing regional and national prestige through achievements in regional, national, and international competitions. Countries worldwide actively pursue sporting success because outstanding athletic performance strengthens international reputation [1]. In Indonesia, football is the most popular sport, leading to the rapid growth of football clubs. The All-Indonesian

Football Association (PSSI) was founded in Yogyakarta on April 19, 1930, under the leadership of Ir. Soeratin Sosrosoegondo, as a response to the Dutch-established Nederland Indische Voetball Bond (NIVB).

The Indonesian national football team is currently competing in the 2026 FIFA World Cup qualification round with a competitive squad. Placed in Group C alongside Japan, Australia, Saudi Arabia, Bahrain, and China, Indonesia achieved notable results, including a 2–0 victory over Saudi Arabia, positioning the team third in the group. In the third qualification round held in March 2025, Indonesia was defeated 1–0 by Australia but subsequently secured victories against Saudi Arabia (2–0) and Bahrain (1–0), demonstrating significant progress [2].

Instagram has become an increasingly popular social media platform in Indonesia and is widely used by supporters of the Indonesian national team to express opinions and support. Analyzing Instagram comments related to the national team provides insights into public sentiment following match results and team policies, which may assist management in strategic decision-making [3].

Previous studies have widely applied the Naïve Bayes Classifier (NBC) for sentiment analysis. Neogi et al. [4] analyzed sentiments related to the Indian farmers' protest using Twitter data, comparing NBC with Decision Tree, Random Forest, and SVM, where Random Forest achieved the highest accuracy. Diekson et al. [5] examined customer reviews on Traveloka using NBC, Logistic Regression, and SVM, with SVM producing the best accuracy. Prajamukti et al. [6] reported that NBC achieved an accuracy of 83% on 232 datasets, while Sidik et al. [7] found NBC accuracy of 64.41% in analyzing sentiments toward the Indonesian national team on Twitter, with predominantly positive sentiment. Nufus [8] also noted that public sentiment toward the Indonesian national team was largely positive due to their performance and dedication. Apryani [9] demonstrated that the Random Forest model outperformed KNN and SVM in sentiment classification, while Franko [10] emphasized NBC as an effective algorithm for sentiment analysis. Other studies highlighted that decision tree models can outperform NBC in recall for positive classes [3], and SVM has also shown strong performance in sentiment classification [11].

Based on these considerations, this study investigates Instagram users' sentiment toward the performance of the Indonesian national football team during the 2026 FIFA World Cup qualification matches, including wins, draws, and losses. The study applies a classifier-based sentiment analysis approach to categorize Instagram comments into positive, neutral, and negative sentiments using the Naïve Bayes Classifier method.

2. CONCEPTUAL FRAMEWORK

2.1 Sentiment Analysis

Sentiment analysis, also referred to as opinion mining, is a methodological approach used to identify and evaluate public emotions, attitudes, or opinions toward a particular issue or object. It involves the extraction and automated processing of textual data to determine whether expressed opinions are positive or negative [12]. This technique is commonly applied to classify reviews and analyze public opinion in online discourse, where opinions often contain both favorable and unfavorable perspectives. The primary objective of sentiment analysis is to interpret views expressed in textual data and to capture individuals' attitudes as reflected in their reactions and preferences toward a specific subject [13]. Additionally, sentiment analysis can be used to summarize reviews by identifying semantic relationships such as synonyms and antonyms within text.

2.2 Techniques for Sentiment Analysis

Sentiment analysis can be performed using various techniques, broadly categorized into machine learning-based and lexicon-based approaches, as illustrated in Figure 1. Machine learning-based methods are further divided into supervised and unsupervised learning, while lexicon-based approaches are classified into dictionary-based and corpus-based methods.

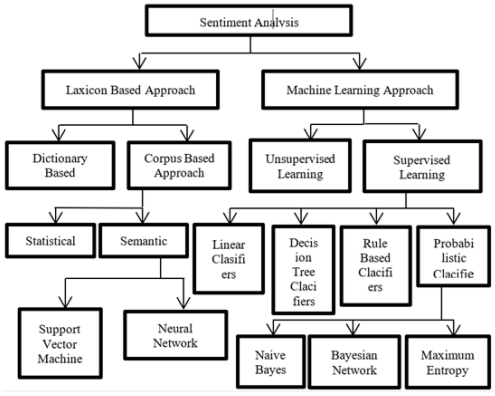


Figure 1. Data Analysis Method [14]

Supervised learning is used when labeled data are available, enabling models to learn from annotated examples and make predictions, whereas unsupervised learning is applied when labeled data are unavailable or unreliable, grouping text based on patterns or keywords. Sentiment analysis is commonly employed to classify reviews and evaluate opinions in textual data, especially in online discourse, capturing both positive and negative sentiments and enabling the summarization of opinions through semantic relationships such as synonyms and antonyms [13].

Lexicon-based approaches provide a simple method for sentiment analysis, where dictionary-based techniques expand sentiment vocabularies using synonyms, and corpus-based approaches infer sentiment orientation from contextual usage through statistical or semantic methods. Sharma et al. [14] highlighted that the choice of sentiment analysis technique should be aligned with the research objectives and scope.

2.3 Sentiment Analysis on Social Media

Sentiment analysis on social media focuses on classifying posts according to expressed polarity, typically as positive or negative. Posts receiving favorable reactions are categorized as positive sentiment, whereas those associated with unfavorable reactions are classified as negative sentiment. This classification process considers both the overall message and the polarity of individual words to identify expressions of negativity or opinions toward specific objects [15]. Social media has proven to be an effective medium for disseminating targeted messages, as sentiment can be assessed by analyzing post structure, content type, substance, and appeal [16]. Moreover, sentiment analysis of social media content can support governmental decision-making in policy implementation, including the enforcement of restrictive measures, as demonstrated in studies analyzing Instagram content related to public policy issues [17].

2.4 Sentiment Analysis Steps

2.4.1 Text Pre-Processing

Text pre-processing transforms unstructured textual data into structured data by reducing dimensionality and improving computational efficiency and accuracy. As an initial stage in text analysis, this process removes elements irrelevant to the document's informational content [18]. According to [19] and [18], the main stages of text pre-processing include: (1) cleaning, which removes punctuation, numbers, hashtags, hyperlinks, usernames, and irrelevant words; (2) case folding, which standardizes all text to lowercase; (3) filtering, which eliminates stopwords to reduce feature dimensionality; (4) tokenization, which splits text into individual word tokens; and (5) stemming, which converts words into their root forms based on the KBBI using the Python Sastrawi package by removing affixes and word variations.

2.4.2 Lexical Cloud

A word cloud is a visual representation of word frequency, where the size of each word reflects its prevalence in the analyzed text [20]. Word clouds are widely used in various fields, including politics, business, and education, as a simple yet effective tool for summarizing and visualizing textual content [21]. By presenting data in an intuitive visual format, word clouds enable researchers and audiences to quickly identify dominant themes and gain insights from social media text, while simultaneously enhancing cognitive engagement and interpretability [21].

2.4.3 Naive Bayes Computation

The general formula for the Naive Bayes theorem is presented in equation 1.

$$P(H|\mathrm{X}) = \frac{P(H|\mathrm{X})P(\mathrm{H})}{\mathrm{P(X)}} \quad (1)$$

Let Xdenote data with an unknown class and Hrepresent a hypothesis that Xbelongs to a particular class. $P(H \mid X)$refers to the posterior probability of hypothesis Hgiven X, $P(H)$is the prior probability, $P(X \mid H)$is the likelihood of observing Xgiven H, and $P(X)$is the probability of X. Bayes' theorem states that a data instance $x$is assigned to the class with the highest posterior probability. Thus, if $P(h_1 \mid x) < P(h_2 \mid x)$, then $x$is classified as h_2. The final classification is determined by comparing the posterior probabilities across all classes [22].

2.4.4 Procedures for Implementing Naïve Bayes in Sentiment Analysis

The implementation of Naïve Bayes in sentiment analysis generally follows several key steps. First, text preprocessing is performed, including case normalization, tokenization, stopword removal, and stemming. Second, data annotation is conducted by manually labeling comments as positive, negative, or neutral to form the training dataset. Third, feature extraction converts textual data into numerical representations using approaches such as Bag of Words (BoW) or Term Frequency–Inverse Document Frequency (TF-IDF). Fourth, class probabilities are calculated; for example, if the training data consist of 30 positive, 50 negative, and 20

neutral comments, then $P(\text{Positive}) = 0.30$, $P(\text{Negative}) = 0.50$, and $P(\text{Neutral}) = 0.20$. Fifth, new comments, such as "The national team achieved a resounding victory," are classified by computing posterior probabilities for each class and selecting the highest value. Finally, model performance is evaluated using accuracy, precision, recall, and F1-score.

3. METHODE

3.1 Research Materials and Instruments

a. Research Materials

This study utilized 1,500 comments collected from the Indonesian National Team's Instagram posts published between September 5, 2024, and March 25, 2025.

b. Research Instruments

The hardware and software specifications used to support sentiment analysis through data mining are as follows. The hardware consisted of a Core i3 dual-core processor (2.53 GHz), a 14-inch monitor, 2 GB RAM, a 1 GB VGA graphics card, a 20 GB hard drive, and a standard optical keyboard and mouse. The software environment included Microsoft Windows 10 as the operating system, Microsoft Office Excel Professional Plus 2016 for dataset preparation, and Notepad++, a Windows-based text editor employing Scintilla components for editing and processing text and source code files.

As shown in Figure 2, the study followed sequential stages: data collection from the Indonesian National Team's Instagram account, text preprocessing, sentiment labeling, descriptive analysis using word clouds, sentiment classification with the Naïve Bayes Classifier, model evaluation using a confusion matrix, and final visualization of dominant word patterns through word clouds.

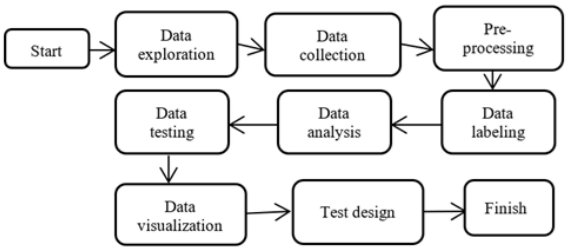


Figure 2. Flowchart for Research Analysis

3.1.1 Data Examination

This study analyzed comment data obtained from the Indonesian National Team's Instagram account. A total of 1,500 comments were collected from posts published between September 5, 2024, and March 25, 2025.

3.1.2 Data Acquisition

Data were collected exclusively using the IG Comment Export Extension on the Google Chrome browser and stored in .csv format. The study employed the Naïve Bayes Classifier methodology. The data acquisition procedure involved installing the IG Comment Export Extension, retrieving the URL of an Instagram post, submitting the link to the extension, exporting comments, and successfully downloading the resulting CSV file.

Limitations and Mitigation of Data Scraping

Instagram does not provide an official public API for unrestricted comment access; consequently, scraping tools can typically retrieve between 500 and 1,000 comments per post, depending on comment density, account type, and browser performance. In addition, Instagram may detect abnormal activities such as rapid or excessive data extraction, leading to incomplete comment loading or temporary account restrictions. To mitigate these issues, several strategies were applied: limiting the number of comments extracted per post to 300–500 and combining multiple CSV files, implementing time delays of 1–2 minutes between scraping sessions, using a well-established Instagram account, ensuring a stable internet connection, and regularly backing up data in CSV or Excel format to prevent data loss.

3.1.3 Preprocessing

Preprocessing constitutes the initial stage following data segmentation and prepares textual data for subsequent analysis. The steps include: (a) cleaning, which removes irrelevant elements such as punctuation, numbers, hashtags, hyperlinks, and usernames; (b) case normalization, which converts all characters to lowercase; (c) filtering, which eliminates stopwords that do not contribute to document classification; (d)

tokenization, which splits text into meaningful tokens for document matrix construction; (e) stemming, which reduces words to their root forms based on the KBBI using the Sastrawi Python package; and (f) lemmatization, which converts words to their canonical forms to improve consistency and measurability in text analysis, as illustrated in Table 1.

Table 1. Lemmatization Table 1. Lemmatization

Term	Comment 1	Comment 2	Comment 3	Document Frequency
National team	1	1	0	2
Played	1	0	0	1
Cool	1	1	0	2
Bad	0	1	0	1
Terrible	0	1	0	1
Enough	0	0	1	1
Satisfied	0	0	1	1
Not good	0	0	1	1

3.1.4 Data Testing/TF-IDF (Term Frequency-Inverse Document Frequency) Weighting

The Term Frequency–Inverse Document Frequency (TF–IDF) algorithm was applied in the word-weighting stage due to its efficiency, simplicity, and reliable performance. This approach calculates Term Frequency (TF) and Inverse Document Frequency (IDF) values for each token in each document to measure the importance of a term. Term Frequency (TF) represents the number of times a word appears within a document, where a higher TF indicates greater term significance and stronger document similarity. The TF–IDF weighting results are presented in Table 2.

Table 2. Illustration of Comment Data (Post-Preprocessing)

No	Original Comment	Preprocessing	Labels
1	"The national team played really well!"	The national team played cool	Positive
2	"The national team played really badly!"	The national team played really badly	Negative
3	"Quite satisfied, but there are still shortcomings."	Quite satisfied, but still lacking	Neutral

1. Term Frequency (TF)

   Term frequency is derived from the count of distinct words in a document (comment), for instance. As in equation 2.

   $$\text{TF} = (\text{above}) = f_{above,\ comment1} / \sum above, comment\ 1 = 1 \quad (2)$$

2. Inverse Document Frequency

   The subsequent stage involves calculating the Inverse Document Frequency (IDF). D represents the aggregate quantity of documents. In this case study, D equals 4. As in equation 3.

   $$\text{IDF} = \log\left(\frac{|D|}{f_{t.d}}\right) \quad (3)$$

Table 3. Example of Inverse Document Frequency Data

Term	Document Frecuency	IDF
National team	2	0.176
Played	1	0.477
Cool	2	0.176
Bad	1	0.477
Terrible	1	0.477
Enough	1	0.477
Satisfied	1	0.477
Not good	1	0.477

3. TF-IDF

Table 4. Example of TF-IDF

Term	TF-IDF		
	Comment 1	Comment 2	Comment 2
National team	0.176	0.176	0
Played	0.477	0	0
Cool	0.176	0.176	0
Bad	0	0.477	0
Terrible	0	0.477	0
Enough	0	0	0.477
Satisfied	0	0	0.477
Not good	0	0	0.477
National team	0	0	0.477

3.1.5 Data Examination

All preprocessing and exploratory analysis stages were conducted using the Python libraries Sastrawi and Wordcloud, selected for their usability and effectiveness. The dataset consisted of Instagram comments related to the performance of the Indonesian National Team. The data analysis procedure comprised several stages. First, data were collected by extracting Instagram comments using tools such as IG Comment Export and stored in CSV format. Second, the data were imported and prepared for analysis. Third, text sanitization was performed by removing punctuation, numbers, URLs, and uppercase letters. Fourth, preprocessing using Sastrawi included stopword removal, elimination of irrelevant words, and stemming to convert words into their root forms. Finally, all cleaned comments were aggregated and visualized using WordCloud to illustrate dominant terms.

3.1.6 Data Validation

Model evaluation was conducted using the confusion matrix to measure accuracy, precision, and recall. The classification model assigns each data instance to its expected class. In binary classification, outcomes are commonly represented as {0,1}, {yes, no}, {+1, −1}, or {positive, negative}. Four possible classification results are obtained: true positive, false negative, true negative, and false positive. A true positive occurs when positive data are correctly classified as positive, while a false negative occurs when positive data are misclassified as negative. Conversely, negative data predicted as negative are considered true negatives, whereas negative data predicted as positive are classified as false positives [23].

Table 5. Actual

	Class	Positive	Negative
Prediction	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

a. Accuracy; The formula for accuracy is represented by the following equation:

$$Accuracy = \frac{TP+FN}{TP+FP+TN+FN} \quad (4)$$

b. Precision; The precision formula can be calculated using the following equation:

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

c. Recall; The recall formula can be calculated using the following equation:

$$Recall = \frac{TP}{TP+FN} Recall = \frac{TP}{TP+FN} \quad (6)$$

3.1.7 Visual Data

This study employed a Word Cloud program for data visualization to identify dominant word patterns and their associations. The visualization was generated from comments collected from the Indonesian National Team's Instagram account. Frequently discussed words were displayed in larger font sizes, while less frequent terms appeared in smaller sizes, enabling rapid identification of prominent themes.

3.1.8 Test Design

All experiments were performed in Google Colab using Python. The workflow included text preprocessing (cleaning, case normalization, filtering, tokenization, stemming, and lemmatization), followed by TF–IDF weighting. The processed data were classified into positive, negative, and neutral sentiments using the Naïve Bayes Classifier, with performance evaluated through accuracy, precision, and recall.

4. RESULT AND DISCUSSION

4.1 Classification Using the Naïve Bayes Classifier

The dataset was split into training and testing sets, after which the Naïve Bayes Classifier was applied for sentiment classification. Model performance was evaluated using a confusion matrix to measure accuracy, precision, and recall. Figure 3 presents the source code output indicating the distribution of sentiment in comments on the Indonesian national team's Instagram posts. Because the data were pre-labeled, the number of sentiment categories can be clearly identified. Table 6 summarizes the sentiment analysis results for Instagram comments corresponding to match outcomes, including wins, draws, and losses.

```
# Split training and testing data (80:20)
X_train, X_test, y_train, y_test =
train_test_split(X_vectorized, y, test_size=0.2,
random_state=42)

# Naive Bayes Model
model = MultinomialNB()
model.fit(X_train, y_train)

# Prediction
y_pred = model.predict(X_test)

# Evaluation: Confusion Matrix and Accuracy
print("Classification Report:")
print(classification_report(y_test, y_pred))

print("Accuracy:", accuracy_score(y_test, y_pred))

# Plot Confusion Matrix
cm = confusion_matrix(y_test, y_pred, labels=['positive',
'negative', 'neutral'])
sns.heatmap(cm, annot=True, fmt='d', xticklabels=['positive'
'negative', 'neutral'],
        yticklabels=['positive', 'negative', 'neutral'],
cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix Naive Bayes')
plt.show()
```

Figure 3 Source Code Coefisien Matrix

Table 6. How Many Sentiment Classes There Are for the Indonesian National Team Win, Draw, and Lose

Centiment Class	Number of Review		
	Win	**Draw**	**Lose**
Positive	39 (7.8%)	32 (7.8%)	69 (13.8%)
Negative	11 (2.2%)	36 (2.2%)	30 (6%)
Neutral	450 (90%)	331 (90%)	401 (80.2%)
Total	500	500	500

The graph illustrates the distribution of positive, negative, and neutral comments on the Indonesian national team's Instagram account across different match outcomes. When the team won, Figure 4.(a) shows that among 500 training comments, 39 were positive, 11 were negative, and 450 were neutral. In the case of a draw, Figure 4.(b) indicates that out of 500 comments, 32 were positive, 36 were negative, and 331 were neutral. When the team lost, Figure 4.(c) shows that from 500 training comments, 39 were positive, 11 were negative, and 450 were neutral.

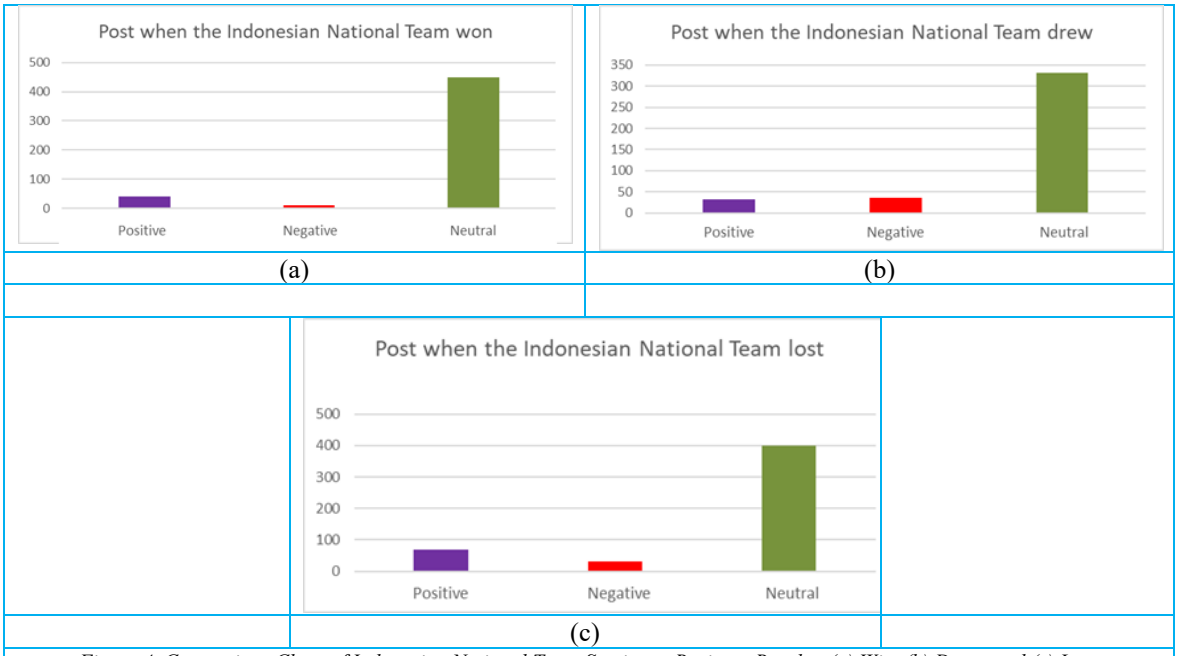


Figure 4. Comparison Chart of Indonesian National Team Sentiment Reviews, Results: (a) Win, (b) Draw, and (c) Loss

4.2 Naïve Bayes Classification

The training data, consisting of positive, neutral, and negative reviews, were analyzed using a classification approach. The Naïve Bayes Classifier learned data patterns based on feature characteristics within each sentiment class. Model performance was then evaluated using a confusion matrix to assess its ability to predict new data. Two testing scenarios were applied, namely data from matches in which Indonesia won and data from matches in which Indonesia lost. Figure 5 shows the source code that goes with the evaluation of the confusion matrix.

```
# Fetch features and labels
X = df['Preprocessed_Comment'].astype(str)
y = df['Sentiment'].astype(str)

# Convert text to numeric feature form with TF-IDF
vectorizer = TfidfVectorizer()
X_tfidf = vectorizer.fit_transform(X)

# Split the data into 80% train and 20% test
X_train, X_test, y_train, y_test = train_test_split(X_tfidf, y,
test_size=0.2, random_state=42)

# Train the Naïve Bayes model
model = MultinomialNB()
model.fit(X_train, y_train)

# Test data prediction
y_pred = model.predict(X_test)

# Calculate confusion matrix and other evaluation
metrics
conf_matrix = confusion_matrix(y_test, y_pred,
labels=["positive", "neutral", "negative"])
report = classification_report(y_test, y_pred,
labels=["positive", "neutral", "negative"], output_dict=True)
accuracy = accuracy_score(y_test, y_pred)

conf_matrix, report, accuracy
```

Figure 5. Source Code for Confusion Matrix Testing

The Naïve Bayes Classifier's results for figuring out the level of accuracy are as follows:

Table 7. Level of Accuracy

	Positive Prediction	Neutral Prediction	Negative Prediction
Original Positive	5	17	0
Original Neutral	0	247	0
Original Negative	0	11	0

Tabel 8. Evaluation Method

Class	Precision	Recall	F1-Score
Positive	**1**	0.23	0.37
Neutral	0.9	**1**	0.95
Negative	0	0	0

Total Accuracy: 90%

4.3 Sentiment Analysis Testing

Sentiment analysis testing was conducted using Google Colab with the Python programming language. The testing aimed to evaluate review data and classify sentiments into positive, negative, or neutral categories, as shown in Figure 6.

```
def label_sentiment(text):
    pos = sum(1 for word in text.split() if word in
positive_words)
    neg = sum(1 for word in text.split() if word in
negative_words)
    if pos > neg:
        return 'positive'
    elif neg > pos:
        return 'negative'
    else:
        return 'neutral'

# Apply to preprocessed comment fields
df["Sentiment"] =
df["Preprocessed_Comment"].apply(label_sentiment)
```

Figure 6. Sentiment Analysis Testing Program Code

The system is able to classify and display positive and negative data samples visually. For example, searching comments associated with “win” yields positive results, while queries containing “lose” retrieve comments classified as negative. Thus, the system effectively groups data by sentiment and presents the classification results clearly.

5. CONCLUSION

This study employed the Naïve Bayes Classifier to analyze sentiment in 1,500 comments from 15 Instagram posts of the Indonesian National Team between September 5, 2024, and March 25, 2025, covering wins, draws, and losses. Sentiment patterns varied by match outcome: positive sentiment dominated during wins (39:11), negative sentiment slightly exceeded positive during draws (32:36), and positive sentiment remained dominant even during losses (69:30), indicating sustained public support.

The model achieved an overall accuracy of 90%, but performance was highly skewed toward the neutral class, with strong precision (0.90), recall (1.00), and F1-score (0.95). In contrast, classification of positive and negative sentiments was weak, reflecting a significant class imbalance that limited the model’s ability to identify minority classes.

Overall, the Naïve Bayes Classifier is effective for capturing general public sentiment toward the Indonesian National Team. Future research should address data imbalance through resampling techniques, apply more advanced classification models, and expand datasets with contextual or multilingual features to enhance sentiment classification performance.

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REFERENCES

[1] M. Riefky and W. Pramesti, "Sentiment Analysis of Southeast Asian Games (SEA Games) in Philippines 2019 Based on Opinion of Internet User of Social Media Twitter with K-Nearest Neighbor and Support Vector Machine," Jurnal Matematika, Statistika Dan Komputasi, vol. 17, no. 1, pp. 26–41, 2020. doi: 10.20956/jmsk.v17i1.9947.

[2] Jnews, "Perjalanan Timnas Indonesia: Sejarah dan Prestasi yang Membanggakan," Lifestyle, 4 December 2024. [Online]. Available: https://jnewsonline.com/sejarah-timnas-indonesia/

[3] R. Aldino and A. M. Chrisdianto, "Analisa Sentimen Timnas Indonesia Menggunakan Metode Naive Bayes Berbasis SMOTE dan Decision Tree Berbasis SMOTE."

[4] A. S. Neogi, K. A. Garg, R. K. Mishra, and Y. K. Dwivedi, "Sentiment analysis and classification of Indian farmers' protest using twitter data," International Journal of Information Management Data Insights, vol. 1, no. 2, p. 100019, 2021. doi: 10.1016/j.jjimei.2021.100019.

[5] Z. A. Diekson, M. R. B. Prakoso, M. S. Q. Putra, M. S. A. F. Syaputra, S. Achmad, and R. Sutoyo, "Sentiment analysis for customer review: Case study of Traveloka," Procedia Computer Science, vol. 216, pp. 682–690, 2023. doi: 10.1016/j.procs.2022.12.184.

[6] R. Prajamukti, "Klasifikasi dan Analisis Sentimen pada Data Twitter Menggunakan Algoritma Naive Bayes (Studi Kasus: Timnas Sepakbola Indonesia Senior, U-23, dan U-19)," Doctoral dissertation, Universitas Pembangunan Nasional Veteran Jakarta, 2021.

[7] M. H. Sidik, S. Widiyanesti, and D. P. Ramadhani, "Analisis Sentimen dan Topic Modelling Terhadap Tim Nasional Indonesia di Kejuaraan AFF Suzuki Cup 2020 Berdasarkan Opini Pengguna Twitter," eProceedings of Management, vol. 9, no. 5, 2022.

[8] R. H. Nufus and U. Surapati, "Analisis Sentimen Persepsi Masyarakat Terhadap Timnas Indonesia U-23 dalam AFC-23 Asian Cup 2024 Pada Media Sosial X Menggunakan Metode Naïve Bayes Classifier," Jurnal Indonesia: Manajemen Informatika Dan Komunikasi, vol. 5, no. 3, pp. 2647–2657, 2024. doi: 10.35870/jimik.v5i3.964.

[9] I. Apryani, A. Fauzi, D. S. Kusumaningrum, and H. H. Handayani, "Analisis Sentimen Performa Timnas Sepak Bola Indonesia pada Kolom Komentar Aplikasi TikTok Menggunakan Algoritma Machine Learning," Jurnal Accounting Information System (AIMS), vol. 8, no. 1, pp. 76–89, 2025. doi: 10.32627/aims.v8i1.1160.

[10] B. Franko, N. Wilyanto, and H. Irsyad, "Analisis Sentimen terhadap Naturalisasi Pemain pada Youtube Menggunakan Decision tree dan Naive bayes," Software Development, Digital Business Intelligence, and Computer Engineering, vol. 3, no. 1, pp. 8–16, 2024. doi: 10.57203/session.v3i1.2024.8-16.

[11] S. Ramadani, "Analisis Sentimen Terhadap Pemain Diaspora Timnas Indonesia Pada Media Sosial Instagram Menggunankan Metode Support Vector Machine (Svm)," Doctoral dissertation, STMIK Widya Cipta Dharma, 2024.

[12] I. F. Rozi, S. H. Pramono, and E. A. Dahlan, "Implementasi opinion mining (analisis sentimen) untuk ekstraksi data opini publik pada perguruan tinggi," Jurnal EECCIS (Electrics, Electronics, Communications, Controls, Informatics, Systems), vol. 6, no. 1, pp. 37–43, 2012.

[13] B. Liu, "A Survey Of Opinion Mining And Sentiment Analysis," Sentiment Analysis, 9781461432, pp. 1–522, 2013. doi: 10.1007/978-1-4614-3223.

[14] D. Sharma, M. Sabharwal, V. Goyal, and M. Vij, "Sentiment analysis techniques for social media data: A review," in First International Conference on Sustainable Technologies for Computational Intelligence: Proceedings of ICTSCI 2019, Singapore: Springer Singapore, 2019, pp. 75-90.

[15] S. Yoo, J. Song, and O. Jeong, "Social media contents based sentiment analysis and prediction system," Expert Systems with Applications, vol. 105, pp. 102–111, 2018. doi: 10.1016/j.eswa.2018.03.055.

[16] A. Molina, M. Gomez, A. Lyon, E. Aranda, and W. Loibl, "What content to post? Evaluating the effectiveness of Facebook communications in destinations," Journal of Destination Marketing & Management, vol. 18, p. 100498, 2020.

[17] T. E. Spillane, B. A. Wong, and D. P. Giovenco, "Content analysis of instagram posts by leading cannabis vaporizer brands," Drug and Alcohol Dependence, vol. 218, p. 108353, 2021. doi: 10.1016/j.drugalcdep.2020.108353.

[18] Y. D. Pramudita, S. S. Putro, and N. Makhmud, "Klasifikasi Berita Olahraga Menggunakan Metode Naïve Bayes dengan Enhanced Confix Stripping Stemmer," Jurnal Teknologi Informasi Dan Ilmu Komputer, vol. 5, no. 3, pp. 269–276, 2018. doi: 10.25126/jtiik.201853810.

[19] S. Kurniawan, W. Gata, D. A. Puspitawati, N. -, M. Tabrani, and K. Novel, "Perbandingan Metode Klasifikasi Analisis Sentimen Tokoh Politik Pada Komentar Media Berita Online," Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi), vol. 3, no. 2, pp. 176–183, 2019. doi: 10.29207/resti.v3i2.935.

[20] R. Atenstaedt, "Word cloud analysis of the BJGP," The British Journal of General Practice, vol. 62, no. 596, p. 148, 2012.

[21] C. Van den Rul, "How to Generate Word Clouds in R: Simple Steps on How and When to Use Them," Towards Data Science, 2019.

[22] A. Imron, "Analisis sentimen terhadap tempat wisata di kabupaten Rembang menggunakan metode Naive Bayes Classifier," 2019.

[23] T. Fawcett, "An introduction to ROC analysis," Pattern Recognition Letters, vol. 27, no. 8, pp. 861–874, 2006. doi: 10.1016/j.patrec.2005.10.010.