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Sentiment Analysis on Indonesian National Football Team Naturalization using KNN and SVM

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Abstract
The naturalization of football players in Indonesia is largely viewed positively, with supporters highlighting its benefits for team performance, international competitiveness, and player development. While PSSI endorses naturalization to strengthen the national team, Liga Indonesia Baru (PT LIB) imposes limits to maintain fairness. The purpose of this research is to examine public sentiment toward the naturalization of Indonesian football players by analysing discussions on X and YouTube. This research analyses public sentiment toward the naturalization of Indonesian football players using a data and text mining approach based on 3,267 comments from X and YouTube between 2022 and 2024. The research process includes data collection, preprocessing, TFIDF, data labeling, and model training and evaluation. Two machine learning models, KNN and SVM, are implemented for classification, with SVM outperforming KNN in accuracy. Our results show that KNN achieved 76.71% accuracy (precision: 52%, recall: 56%, F1-score: 53%), while SVM RBF outperformed with 86.51% accuracy (precision: 59%, recall: 42%, F1-score: 26%). SMOTE and GridSearch effectively address the class imbalance and optimize model performance. Public sentiment is predominantly positive, highlighting enhanced team performance and global recognition. These insights assist PSSI and policymakers in making informed decisions regarding fairness, discrimination, and the governance of Indonesian football.

Keywords: naturalization; social media analysis; text classification; *timnas*

INTRODUCTION

The naturalization of football players in Indonesia has become a major topic of discussion, particularly as a strategy to strengthen the national team (Zahran et al., 2024). The Indonesian Football Association (PSSI) actively pursues naturalization following Regulation Number 3 of 2019 on the Acceleration of National Football Development, which allows foreign players to obtain Indonesian citizenship if they meet specific criteria. PSSI aims to bridge the gap in player quality (Sofiyan et al., 2024), improve Indonesia's FIFA ranking, and enhance competitiveness in international tournaments such as the AFF Championship, Asian Cup, and World Cup qualifiers (Annas & Hazzar, 2024). However, this policy has sparked debates among football enthusiasts and the public regarding its impact on local player development and the long-term sustainability of Indonesian football. Social media has amplified discussions on this issue, reflecting both support and criticism as naturalization continues to shape the composition of the Indonesian national team; it remains a crucial subject for further analysis and debate (Aneboa et al., 2024).

Despite PSSI's support for naturalization, Liga Indonesia Baru (PT LIB) has introduced a regulation limiting each club to registering only two naturalized players in the 2023–2024 Liga 1 season (Annas & Hazzar, 2024). This decision has sparked public debate, as many believe it contradicts the Human Rights principles (HAM). The Indonesian U-20 national team has 11 naturalized players from various countries, raising concerns over their limited opportunities in domestic leagues. The Indonesian Professional Footballers Association (APPI) has publicly criticized this restriction, arguing that it violates HAM because naturalized players, having obtained Indonesian citizenship, should have the same rights as indigenous citizens (Annas & Hazzar, 2024). Additionally, this regulation distinguishes native and naturalized players, treating the latter similarly to foreign national players, which further fuels criticism (Sania et al., 2025).

The perceived discrimination has led to widespread discussions among football fans, media, and stakeholders, reinforcing the role of public opinion in challenging policies that may be deemed unfair (Angumboro & Wakhid, 2024). As a result, the debate over naturalization and player restrictions has intensified, influencing public perception and potentially shaping future policy decision (Erwansyah et al., 2024). To understand public sentiment on this issue related to differences in public perceptions of the naturalization of football players in Indonesia. This research proposes a machine learning-based approach that integrates data mining and text mining as an effective solution for analyzing public opinion objectively by applying the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) algorithms (Wicaksono et al., 2023). By leveraging these techniques, researchers can extract insights from unstructured social media data, enabling an objective, scalable, and data driven sentiment analysis. This method eliminates the limitations of manual sentiment classification, such as bias and inconsistency, while handling large datasets efficiently (Khairunnisa et al., 2021).

The analysis follows a process approach, beginning with data preprocessing, which includes cleaning, case folding, normalization, stopword removal using Sastrawi, and stemming from refining the text data (Khairunnisa et al., 2021). After preprocessing, TF-IDF is used to extract relevant features from the text (Irawaty et al., 2020). After TF-IDF, data labeling assigns positive, negative, and neutral labels to text data (Solimun et al., 2023). The processed data is then classified to help improve the analysis of machine learning algorithms, KNN, and SVM to determine public sentiment. The choice of SVM and KNN is based on their effectiveness in text classification. SVM offers strong and simple generalizations (Rabbani et al., 2023). KNN serves as a benchmark method for comparison (Putra & Dwiki, 2021), making this research provide policymakers and PSSI insights into understanding public perceptions and formulating more appropriate policies.

Based on the results of previous research discussing the naturalization of the Indonesian national team using the SVM method with a X dataset of 100 comments, achieved 71% accuracy (Ghafur et al., 2025). Meanwhile, other discussing the naturalization of players on YouTube using the Decision Tree and Naive Bayes methods resulted in an accuracy of depth worth 3 of 70%, depth worth 4 of 71.8%, depth worth 5 of 70.9%, and the naive bayes method of 85.4% research (Franko et al., 2024). However, these studies were limited in scope, either by dataset size or focusing on a single social media platform. This research addresses a limitation in previous research by combining Twitter and YouTube data sources to analyze sentiment regarding Indonesian football player naturalization, unlike prior research focused on a single platform.

The purpose of this research is to examine public sentiment toward the naturalization of Indonesian football players by analyzing discussions on X and YouTube. Unlike previous research that only used one data source, this research combines data from X and YouTube to provide a broader perspective. As the naturalization policy triggers debates on human rights and public perception, this analysis provides insights for policymakers, sports analysts, and PSSI in making more informed decisions regarding fairness, discrimination, and governance of Indonesian football.

METHOD

This research was conducted to analyze sentiment data obtained through crawling from API X, which collects many tweets that can be further analyzed to understand user behaviour and perceptions on various topics (Arolfo et al., 2022). This API facilitates direct access to Twitter data not limited to public tweets, allowing researchers to perform in-depth analysis with natural language processing and machine learning techniques and YouTube between 2022 and 2024. Initially, the research aggregates data from X and YouTube concerning the Naturalization of the Indonesian Football National Team by crawling X with the keywords' *naturalisasi timnas'* and *'pemain naturalisasi'* as well as YouTube videos titled *"Pemain Keturunan Baru Timnas Indonesia yang Bakal Bungkam Semua Kritik"* and "*Demi Kedalaman Skuad! Pemain Keturunan Ini Bisa Gabung Timnas Indonesia"* from the Starting Eleven Story Channel chosen due to its high engagement and relevance to the research topic. The data crawling technique yielded 1732 X posts and 1912 Youtube comments.

The preprocessing phase used the NLTK and Sastrawi libraries to clean unnecessary elements such as mentions, hashtags, links, numbers, and special characters. Case folding was applied to convert all text to lowercase for uniformity. Tokenization using NLTK splits the text into individual words to facilitate further processing. Normalization was performed with a predefined dictionary to correct misspellings. Stopword removal using the Sastrawi library eliminated common words that do not contribute to sentiment analysis. Lastly, stemming was applied with the Indonesian language stemmer to reduce words to their root forms, ensuring consistency and improving sentiment classification accuracy.

Term Frequency-Inverse Document Frequency (TF-IDF) is a feature extraction method applied to natural language processing to measure the significance of terms in a document about a text of documents. The parameters used in TF-IDF include ngram_range = (1,2), which considers both unigrams and bigrams to capture meaningful phrases while reducing noise. The TfidfVectorizer transforms the text into a numerical representation, assigning weight to each word's significance. The resulting matrix encapsulates the weight of words within the dataset, and the inverse document frequency (IDF) values are obtained to ascertain the prevalence or scarcity of each phrase across all documents. In this research, TF-IDF was chosen over Bag of Words or word embeddings for its efficiency in handling sparse data and highlighting important words without high computational costs (Cahyani & Patasik, 2021).

Sentiment labelling was performed using a lexicon-based approach with the Indonesian Sentiment (INSET) Lexicon, categorizing text as positive, negative, or neutral. The dataset was then split into training (70%), validation (15%), and testing (15%) subsets (Wongvorachan et al., 2023). Since class imbalance was observed, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to balance sentiment distribution, increasing the dataset to 6,330 samples (Rikky et al., 2024). KNN and SVM were used for classification, with RandomizedSearchCV for optimizing hyperparameters. Performance was evaluated using a Confusion Matrix (accuracy, precision, recall, F1-score) and a heatmap visualized error rates and accuracy, ensuring a robust sentiment analysis of Indonesian football player naturalization.

RESULTS AND DISCUSSION

Result

The data crawling process will produce 1723 X and 1912 YouTube comment data taken with a time interval of 2022 and 2024 using a Python crawler from API X. This method can facilitate the data crawling process because there is no X limitation in the crawling process, and the results can be stored in the form of CSV files and Excel files. The dataset, as shown in table 1, consists of comments, including discussions on naturalization in Indonesian football and various perspectives on its effectiveness and impact.

Table 1. Data crawling x and youtube

Date & Time	Comment
Thu Nov 07 11:30:00 +0000 2023	*@kegblgnunfaedh TANDA TANGAN DOKUMEN NATURALISASI SAMA PERSETUJUAN AJA SAMPAI SITU SAJA KERJA KALIAN GA USAH YG LAIN KALO TIDAK MENGERTI EFEKTIVITAS NATURALISASI DI ERA PSSI SEKARANG*
Thu Nov 07 10:24:13 +0000 2024	*@tehmanis Naturalisasi bagus sih menurut sy krn energinya mantap dan jos kayak yang di jerman* 😅 😅 😅 😅 😅 😅

After collecting 3,267 datasets, the next step is data preprocessing, which includes data cleaning, case folding, normalization, stopword removal, tokenize, and stemming. The Indonesian stemming process using the Sastrawi library helps convert words into their base form, thus improving the accuracy of the analysis. Case folding and tokenization are performed using the Natural Language Toolkit (NLTK) to convert text to lowercase and separate words. In addition, stopword removal uses a list of common words from Sastrawi, which can be expanded with additional words as needed. With these steps, the data used in the analysis becomes cleaner and more structured, thus improving the performance of the classification algorithm.

Table 2. Preprocessing result

Preprocessing Process	Result
Raw Dataset	*@PutraKelana Klo full skuad saya tunggu timnas inti Formasi 3-4-3 biar JOS*
Data Cleaning	*Klo full skuad saya tunggu timnas inti Formasi 3-4-3 biar JOS*
Case Folding	*klo full skuad saya tunggu timnas inti formasi 3-4-3 biar jos*
Normalization	*[’klo’, ’full’, ’skuad’, ’saya’, ’tunggu’, ’timnas’, ’inti, ’formasi’, ’3-4-3, ’biar’, ’jos’’]*
Stopword removal	*['full', 'skuad', 'tunggu', 'timnas', 'inti', 'formasi', '3-4-3']*
Tokenization	*['full', 'skuad', 'tunggu', 'timnas', 'inti', 'formasi', '3', '4', '3']*
Stemming	*['full', 'skuad', 'tunggu', 'timnas', 'inti', 'formas', '3', '4', '3']*

Table 3 shows the sentiment classification of comments using INSET Lexicon, where comments with negative scores are categorized as Negative, zero as Neutral, and positive as Positive. The comment "*naturalisasi bukti omong kosong negara*," with a score of -6, is categorized as Negative because it contains the word "*omong kosong*." The comment "*mantap*" with a score of 0 is categorized as Neutral because it does not have a strong sentiment charge. The comment "*beri rekomendasi naturalisasi atlet sepak bola*," with a score of 12, is categorized as Positive because it contains the word "*rekomendasi*" with a value of 5 and "*atlet*" with a value of 7. After this classification is done, TF-IDF is used to give additional weight based on the importance of the word in the dataset.

After classifying the data labelling with positive, negative, and neutral classes, perform the TFIDF, which assigns weight to words based on their importance in the dataset. This research implemented TF-IDF using the TfidfVectorizer function from the Scikit-learn library with the parameters ngram_range = (1,2). This function considers unigrams (single words) and bigrams (two-word combinations) to capture meaningful phrases while reducing noise. In Table 4, the "Term" shows the results of TF-IDF calculation for some words in the document. The Term column contains the analyzed word, while the D1 - D6 column shows the Term Frequency, which describes how often the word appears in each document. The DF column shows the number of documents containing the word, where all words in the table have DF, which means each word appears in only one document. The IDF column shows the importance of the word in the overall document, where the smaller the DF, the higher the IDF, indicating that the word appears less frequently and is considered more important in the analysis.

Table 3. Sentiment classification

Comment	Lexicon Value	Label	Sentiment Words & Scores
naturalisasi bukti omong kosong negara	-6	Negative	*omong kosong(-6)*
mantap	0	Netral	*mantap(0)*
beri rekomendasi naturalisasi atlet sepak bola	12	Positive	*rekomendasi(5), atlet(7)*

Table 4. TFIDF result

Term	TF						DF	IDF
	D1	D2	D3	D4	D5	D6		
pssi		0,6782		0,2145			1	0,7782
naturalisasi	0,1245		0,6321		0,2123		1	0,8882
				....				
pemain	0,2234			0,3456			1	0,5678

The following process is the split data process, which is divided into 70% training data, 15% validation data, and 15% test data. The training set is utilized to fit the model, the validation set is used to optimize hyperparameters and evaluate performance during development, and the test set functions as a final assessment to gauge generalization. After completing the SMOTE technique with an even division, the dataset is 2110:2110:2110. After that, the evaluation process of the KNN algorithm method and 3 SVM kernels will proceed with datasets that have been SMOTE and GridSearch. The evaluation metrics used include Accuracy, Precision, Recall, and F1-Score, which assess the model's ability to classify data effectively. The evaluation results of both methods can be seen in tables 5 and 6.

Table 5. Evaluation of the knn methods

Method	Accuracy	Precision	Recall	F1-Score
KNN	76%	52%	56%	53%

Table 6. Evaluation of the svm methods

Kernel	Accuracy	Precision	Recall	F1-Score
Linear	84%	59%	42%	26%
RBF	86%	59%	42%	26%
Polynomial	21%	59%	42%	26%

According to table 5, the KNN model with a parameter value of K = 5, optimized through GridSearch and SMOTE, achieves an accuracy of 76%. This performance is inferior to SVM, particularly in managing sentiment variability. With a precision of 52%, recall of 56%, and F1-score of 53%, this model exhibits deficiencies in effectively discerning sentiment. The macro average F1-score is also lower than SVM, suggesting less consistent performance across all sentiment categories. In summary, SMOTE and GridSearch mitigate class imbalance and enhance model performance; the SVM model remains superior to KNN. The data visualization of the evaluation results of both methods can be seen in Figure 3.

Additionally, table 6 presents the evaluation of SVM models with different kernels. The Linear and RBF kernels achieved higher accuracy 84% and 86% than the Polynomial kernel 21%. However, all three models have the same Precision 59%, Recall 42%, and F1-Score 26%. The RBF kernel achieved the highest accuracy 86%, followed by the linear kernel 84%; all three kernels revealed equivalent Precision 59%, recall 42%, and F1-score 26%. This suggests that the reported values are likely macro averages, meaning that each class's metrics are computed separately and then averaged without considering class imbalance. The RBF and Linear kernels outperform the Polynomial kernel because they more effectively identify decision boundaries. The RBF kernel is particularly useful for capturing non-linear relationships, which is common in sentiment analysis tasks. Meanwhile, the Polynomial kernel struggles to generalize, likely due to overfitting or an inappropriate degree selection, leading to poor overall performance.

One of the primary reasons KNN underperforms is its distance-based algorithm, making it highly sensitive to high-dimensional feature spaces, such as TF-IDF representations used in text classification. Unlike SVM, which aims to find an optimal decision boundary, KNN relies on neighbouring data points. This can lead to misclassification, particularly when sentiment data points are closely distributed, making it difficult for KNN to distinguish between similar sentiments.

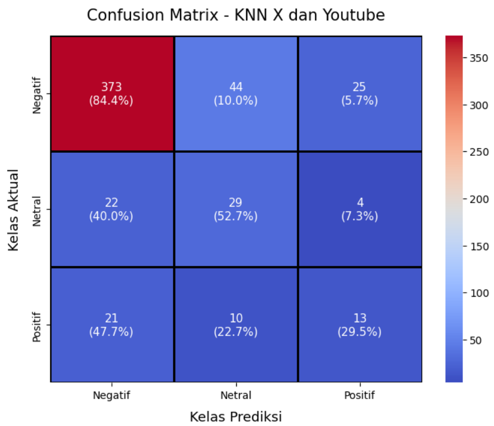

Figure 1. Visualization of knn method

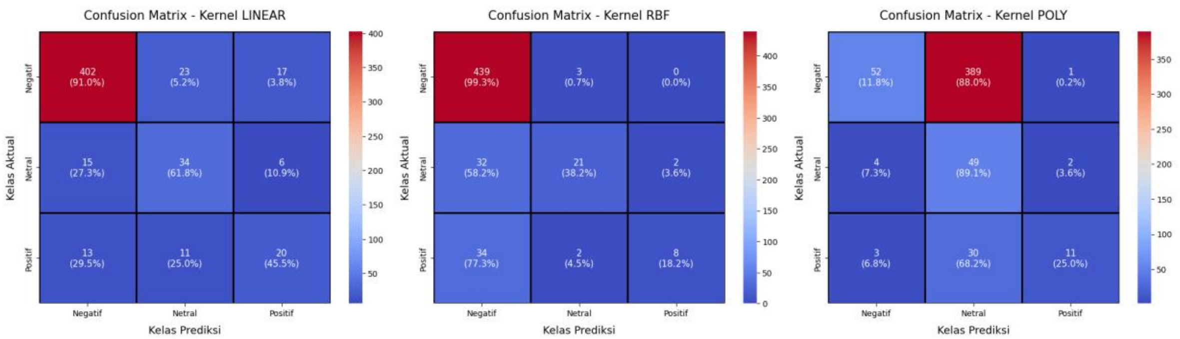

Figure 2. Visualization of svm method with 3 kernel

Figure 1 shows the performance of the KNN model. Compared to the SVM model, KNN shows lower classification accuracy, especially in distinguishing neutral and positive sentiment classes. The model correctly classifies 373 negative predictions but misclassifies 44 as neutral and 25 as positive. Similarly, KNN correctly classifies 29 predictions for neutral sentiments, but 22 are misclassified as negative and 4 as positive. Regarding positive sentiments, the model correctly classifies 13 predictions, but 21 are misclassified as negative and 10 as neutral, indicating that KNN's distance-based approach fails in high-dimensional sentiment analysis. These errors can lead to misinterpretations in sentiment trends.

Figure 2 presents the confusion matrices for AUC-ROC analysis of the confusion matrices of three SVM kernels (Linear, RBF, and Polynomial); the RBF kernel performs best in distinguishing sentiment classes. The Linear kernel has a moderate AUC because although it classifies negative sentiments well (91.0%), it still struggles to distinguish neutral (61.8%) and positive (10.9%) classes. The RBF kernel has the highest AUC as it achieves high accuracy in the negative class (99.3%) while still providing a better balance in classifying the neutral (38.2%) and positive (18.2%) classes than the other kernels. Meanwhile, the Polynomial kernel has the lowest AUC as it tends to overfit the negative class (88.0%) and fails to accurately recognize the neutral and positive classes, making it less suitable for balanced sentiment analysis. Overall, RBF SVM is the best choice for sentiment classification.

Discussion

This research analyzes sentiment classification performance using data from X and YouTube, focusing on the naturalization of Indonesian football players. The dataset comprises 1,732 entries from X and 1,912 from YouTube. A thorough preprocessing stage, including cleaning, normalization, tokenization, stopword removal, and stemming, ensured high data quality before feature extraction using TF-IDF. This step significantly contributed to model performance by reducing noise and standardizing text data. The dataset was split into training (70%), validation (15%), and testing (15%) sets to enhance generalization and address class imbalance. Sentiment classification results show that positive sentiments dominate, with over 2,000 instances, while negative sentiment accounts for approximately 1,000 entries. Neutral sentiment forms the smallest category, highlighting classification challenges due to language ambiguity, sarcasm, and irony.

Two machine learning models, SVM and KNN, were used to assess classification effectiveness. SVM outperformed KNN across all performance indicators; the evaluation metrics, comprising accuracy, precision, recall, and F1-score, demonstrate that the SVM model surpasses KNN in all performance indicators. Specifically, the SVM attained an overall accuracy of 87% and a macro-averaged F1-score of 69%, indicating enhanced classification efficacy. Although the model significantly classifies negative cases, it still has trouble differentiating between neutral moods, which may be an area for improvement. With the highest accuracy 86% among the three SVM kernels, the RBF kernel exhibited the highest accuracy 86%, highlighting its capability to capture complex patterns in the data. The linear kernel followed closely with 84% accuracy, making it a reliable choice for linearly separable data. In contrast, the polynomial kernel performed poorly 21% accuracy, likely due to overfitting or inappropriate selection of polynomial degrees. While all three kernels displayed similar precision 59%, recall 42%, and F1-score 26%, the accuracy gap suggests that kernel selection significantly impacts model performance.

Conversely, KNN achieved 76% accuracy but struggled with neutral sentiment classification, resulting in a lower F1 score of 53%. Misclassification patterns suggest that neutral sentiments often overlap with weakly positive or negative expressions, making them harder to distinguish. This suggests that KNN, although a suitable alternative for distinguishing between sentiment classes, especially neutral ones, overall, SVM proved to be a superior model for sentiment classification, offering better results and classification accuracy. At the same time, the difficulty hindered KNN's performance in distinguishing between different sentiment categories.

Performing SMOTE and GridSearch techniques enhances accuracy compared to previous research utilizing the same methods, KNN and SVM, which achieved accuracies of 71% and 83% (Putri et al., 2024), and other studies using KNN and SVM achieving accuracies of 71% and 80% (Pamungkas & Cahyono, 2024). This study demonstrates that the SMOTE technique enhances prediction accuracy by mitigating class imbalance through synthetic minority class examples. Simultaneously, GridSearch systematically optimizes model parameters, leading to improved predictive performance. Both models encountered challenges in accurately classifying neutral sentiments, a common issue in sentiment analysis due to linguistic ambiguity, sarcasm, and irony. Misclassification patterns indicate that neutral sentiments often overlap with weakly positive or negative expressions, posing difficulties for accurate distinction by the models. SVM's superior performance can be attributed to its ability to establish clear decision boundaries, whereas KNN, relying on distance-based metrics, struggles with subtle variations in sentiment.

The findings hold significant implications for PSSI and football policymakers, understanding public sentiment on player naturalization can help policymakers and PSSI make more informed decisions regarding fairness, discrimination, and governance of Indonesian football. While sentiment is generally positive, concerns about fairness in player selection and national identity persist. Implementing sentiment analysis tools can help PSSI monitor public perception and refine communication strategies.

CONCLUSION

The research compares the effectiveness of SVM and KNN in sentiment classification. Among the SVM kernels, the RBF kernel performed best at 86% accuracy, followed by the linear kernel at 84%. In contrast, the polynomial kernel performed poorly at 21% accuracy, KNN with 76% accuracy, struggled particularly with neutral sentiment classification, while SVM’s superior decision boundary capability helped improve classification accuracy. The research also highlights the effectiveness of SMOTE and GridSearch in addressing class imbalance and optimizing model performance. The dominance of positive sentiment indicates strong public support for naturalization, which PSSI and football policymakers can leverage to reinforce policies that enhance team performance and international competitiveness. However, challenges remain in accurately distinguishing neutral sentiments, suggesting that additional data mining techniques or machine learning approaches be incorporated into future research.

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