Sentiment Analysis of Public Responses on Social Media to Satire Joke Using Naive Bayes and KNN

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Abstract: This study examines the use of Satire Joke as a humorous communication style in conveying criticism of the government through social media. Satire Joke is often used to depict the government's inability to address important social issues, such as slow bureaucratic processes and unfulfilled political promises. The purpose of this research is to see how people behave towards Satire Jokes posted on the YouTube social media platform. Naive Bayes and K-Nearest Neighbors (KNN) methods are used in this research due to their effectiveness in classifying data. It is expected that the results of this research will increase general knowledge and improve understanding of social issues relevant to society. In addition, it is hoped that this research will help future sentiment analysis methods. The analysis results show that there are 400 data with neutral sentiment, 850 data with negative sentiment, and 947 data with positive sentiment. Based on testing, both Naive Bayes and KNN methods showed satisfactory performance, with Naive Bayes achieving the highest accuracy of 90.29%, while KNN achieved an accuracy of 60.75%.

Keywords: Satire Joke, Sentimen Analysis, Government criticism, social media, Naïve Bayes

INTRODUCTION

Satire Joke is a humorous communication style used to indirectly convey opinions to the criticized party. Satirical humor is often employed on social media platforms such as Twitter, Facebook, and YouTube as a subtle tool for criticism (Suciartini, 2019). This form of humor frequently highlights social issues and critiques the actions of public officials and prominent figures, thereby significantly influencing public perception (Dodalwa, 2019). Criticism through satire typically targets bureaucratic inefficiency, complex policies, and unfulfilled political promises, using irony and humor to underscore dissatisfaction with governmental performance (Dodalwa, 2019).

This phenomenon underscores satire as a crucial tool for communicating public discontent with the government. However, despite its popularity, research specifically examining public responses to satirical content on social media, especially YouTube, remains limited. Previous studies have largely focused on sentiment analysis using methods such as Random Forest and Naïve Bayes classifiers, demonstrating significant improvements in accuracy and precision (Alita & Isnain, 2020) (Sherly Christina, 2019).
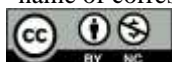
Yet, there are shortcomings in applying Naïve Bayes and K-Nearest Neighbors (KNN) methods to classify YouTube comments criticizing public officials through satire. The issue addressed in this research is the lack of comprehensive analysis of public sentiment towards satirical content on YouTube, particularly comments criticizing public officials. This research gap means that we do not fully understand how the public perceives and reacts to satirical critiques of governance on such a prominent platform.

This incomplete understanding can hinder policymakers in grasping nuanced public opinions conveyed through satire, potentially leading to mismatches between public sentiment and policy responses. Without this understanding, policymakers may fail to capture fundamental concerns expressed by the public through satirical humor.

This study aims to fill this gap by developing an application for sentiment analysis of public opinions from YouTube. Utilizing the Naïve Bayes method, known for its robust classification capabilities (Lunando & Purwarianti, 2013), while K-Nearest Neighbors (KNN) as well as the KNN method, recognized for its ability in self-learning and data categorization (Ernawati & Wati, 2018). this research seeks to enhance understanding of societal attitudes towards governance issues conveyed through satire.

In this study,the researchers aim to compare the Naive Bayes algorithm and K - Nearest Neighbors (KNN) algorithm in classifying Youtube comments, By exploring sentiment analysis within the context of satirical discourse on social media, this research not only contributes to the development of sentiment analysis methodologies but also provides crucial insights for more informed public discussions and policy formulation.

LITERATURE REVIEW

In their study, Riyadi, Selamet, Utami, Ema, and Yaqin (2023) conducted a comparison between Support Vector Machine (SVM) and Naive Bayes algorithms, incorporating various feature selection techniques. They utilized Multinomial Naive Bayes (MNB) for the Naive Bayes algorithm and SVM with a polynomial kernel of degree 3. Their findings indicated that MNB achieved higher accuracy compared to SVM. Specifically, MNB attained an accuracy of 83.85% without feature selection, which improved to 90.77% with feature selection using the chi-square technique (Riyadi, Selamet; Utami, Ema; Yaqin, 2023).

The results of the study (Alfaris, 2023) demonstrate that both K-Nearest Neighbors and Naïve Bayes Classifier are viable for sentiment analysis of Shopee application reviews on Playstore, achieving an accuracy of 70.00%. The test dataset comprised 400 samples, including 268 negative and 132 positive reviews, suitable for K-Nearest Neighbors' application. However, using the same dataset, Naïve Bayes Classifier attained a slightly higher accuracy of 71.00%. Based on the analysis, it can be concluded that Naïve Bayes Classifier outperforms K-Nearest Neighbors with its accuracy rate of 71.00%. The study also compared the accuracy results of both algorithms separately: KNN achieved 49.65%, whereas Naïve Bayes Classifier achieved 71.00%.

Research conducted by Tiara Sari Ningsih (Ningsih, Sari, Tiara et al, 2024) comparing Naive Bayes (NBC) and Support Vector Machine (SVM) classification models. Data processing was performed using the Python programming language. The analysis results show that SVM recorded higher accuracy than NBC for MyTelkomsel (77% versus 75%) and MyXL (76% versus 72%) applications. In contrast, NBC showed higher accuracy for MyIM3 application, reaching 80%.

The test results showed that the Support Vector Machine (SVM) classification method achieved higher accuracy compared to the K-Nearest Neighbors (KNN) method. Specifically, SVM achieved an accuracy value of 88% for Waterbom Bali, 83% for Mandala Suci Wenara Wana, 89% for Tegalalang Terraces, 88% for Tanah Lot Temple, and 95% for Uluwatu Temple. (Sari,A, Hermanto; T,Defriani, 2023).

The results of data classification of Indonesian people's responses to the Covid-19 pandemic on Twitter social media using the support vector machine algorithm with a linear kernel and 10-fold cross validation model evaluation showed an accuracy of 90.1%. If using the naive bayes algorithm with laplace 1 correction and 10-fold cross validation model evaluation, the resulting accuracy is 79.2%. Meanwhile, using the K-nearest neighbor algorithm with a parameter k of 20 and a 10-fold cross
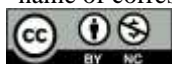
validation model evaluation resulted in an accuracy of 79.2%. The 10-fold cross validation model evaluation resulted in an accuracy of 62.1% (Sodik & Kharisudin, 2021).

In this study (Nijunnihayah, U; Hilabi, S; Nurapriani, 2024), the use of a data mining application with a K-Nearest Neighbor approach to predict the sales of medical devices through a medical device-specific platform resulted in an accuracy rate of 95.00%. This prediction was done using RapidMiner on truly relevant medical device data. With such a high accuracy rate, the K-Nearest Neighbor method proves to be an effective tool in forecasting medical device sales. The prediction results show that this method is reliable for future sales planning.

METHOD

This study compares and contrasts the effectiveness of the Naive Bayes and K-Nearest Neighbors algorithms in determining the most accurate method. Figure 1 illustrates the steps taken in order to conduct the research.
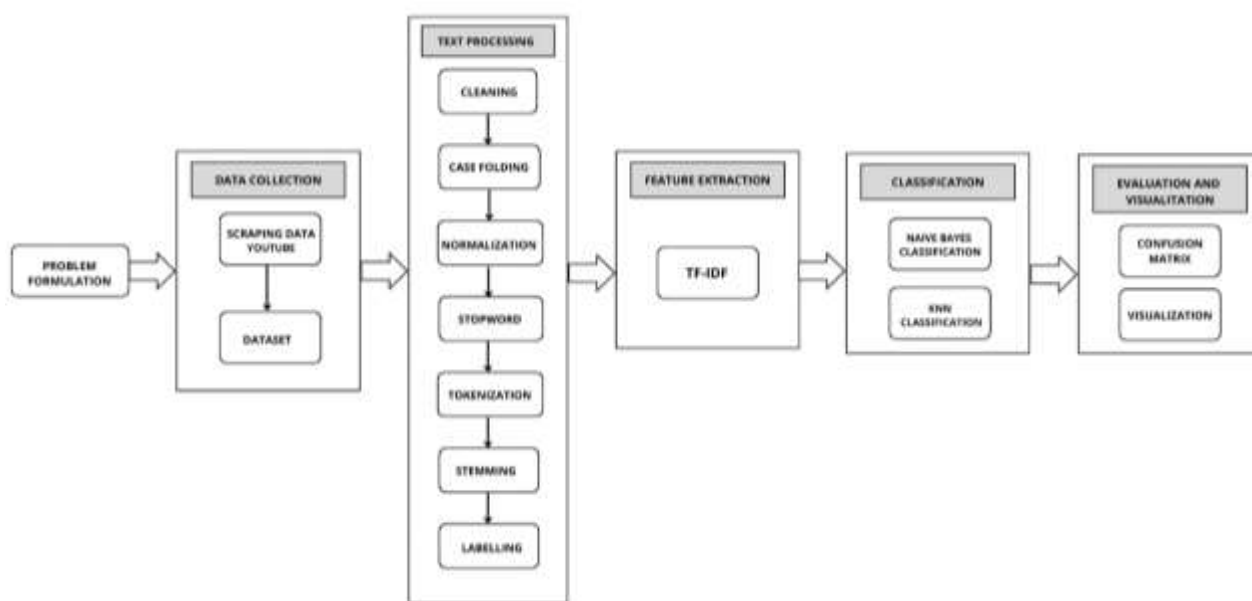

Fig. 1 Research Process Design

The data collection process begins with internet research. Subsequently, preprocessing involves six stages: data cleaning, tokenization, normalization, case folding, removal of stopwords, and stemming. Following preprocessing, the TF-IDF method is applied to extract features for the labeling process, categorizing data into neutral, negative, and positive categories. Classification is then conducted using Naive Bayes and K-Nearest Neighbor algorithms. Evaluation is carried out using the Confusion Matrix to assess accuracy, precision, recall, and F1 score for both Naive Bayes and K-NN datasets. Finally, analysis is performed based on the collected data to draw conclusions.

Problem Formulation

This problem formulation incorporates the findings of a literature review focusing on sentiment analysis related to satire jokes on YouTube. The research problem is clearly outlined and relevant due to people's reactions to government performance, controversies, and economic consequences. TF-IDF clustering and comparison of Naive Bayes and K-Nearest Neighbor methods are used to apply sentiment analysis methods. This research aims to find dominant perspectives, key debates, and sentiment patterns regarding satire jokes on YouTube. Therefore, it is expected that this research will provide a solid foundation for achieving research objectives, overcome the lack of knowledge, and make an important contribution to the understanding of public opinion on social media..

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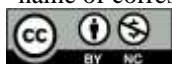
Data Collection

This research uses public opinion data from Deddy Corbuzier's YouTube channel. Data is collected through scraping techniques with the youtube_comment_downloader python tool, and the opinions used are Indonesian opinions.

Text Preprocessing

After successfully collecting comments from YouTube channels, the next important step is to pre-process the data for further sentiment analysis. This process includes several detailed steps as follows (Jiawei Han, Micheline Kamber, 2012):

Step-1: Cleaning The cleaning stage, is done by removing punctuation, unnecessary characters, replacing misspelled words, and removing duplicate data.

Step-2: Case Folding Case folding stage, all letters in the document are converted to lowercase. Only letters from 'a' to 'z' are retained. Non-alphabetic characters are removed and treated as delimiters.

Step-3: Normalization Normalization Stage, this process converts words in the text into their standard form. It is done to address variations in the spelling of words that have the same meaning.

Step-4: Stopword Stopword removal or filtering stage, This stage involves removing irrelevant words from the tokenization results. This can be done using a stoplist algorithm (removing less important words) or wordlist (retaining important words). Stoplists or stopwords are words that do not provide a significant description and can be ignored.

Step-5: Tokenization Tokenizing Stage, Used for truncation based on the input string of each word that forms it.

Step-6: Stemming stemming stage, this process converts the words in the text into basic forms or root words. The aim is to reduce dimensionality and speed up the analysis process by removing inflected words.

Step-7: Labelling Data labeling stage, is an important step in sentiment analysis that involves labeling the data based on the sentiment contained in it. This process is usually done after the preprocessing stage, where texts will be classified as positive, negative, or neutral based on their context.

Word Weighting

The purpose of the feature extraction stage is to prepare the data for the categorization process. In this research, the TF-IDF (Term Frequency-Inverse Document Frequency) method is used to weight the words in the context of the document. This method combines two concepts: Inverse Document Frequency (IDF) and Term Frequency (TF) (M. R. D. Faisal, 2022). In addition, TF-IDF allows greater focus on words that appear frequently in a particular document (M. R. D. Faisal, 2022). Thus, this technique increases accuracy in text processing and document clustering.
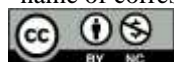
Naïve Bayes

Naive Bayes is a widely used classification method in data mining and statistics. It applies Bayes' theorem assuming that each attribute used in classification is independent. In the classification process, Naive Bayes calculates the probability of each class for every data instance and predicts the class with the highest probability as the final outcome (Kusrini. and E. Luthfi, 2019). This approach is represented by formula (1) (Kusrini. and E. Luthfi, 2019). Where, X represents a data sample with an unknown class label, H denotes the hypothesis that X belongs to class (label) C. P(H) denotes the probability of hypothesis H, $P(X)$ represents the probability of observing the data sample, and $P(X|H)$ indicates the probability of data sample X, given the hypothesis H is true.

$$P(H \mid X) = \frac{P(X|I)P(H)}{P(X)} \tag{1}$$

K – Nearest Neighbors

The k-NN algorithm utilizes the Euclidean Distance method to compute distances between pairs of data points. Greater distances indicate greater similarity between the data points (Riadi et al., 2020). The distance between training data and new input data (test) is computed using the Euclidean Distance

formula. Subsequently, the data is sorted in ascending order, and the value of k determines the boundary of the nearest neighbor distance space. The k value specifies how many nearest neighbors are considered, with the most frequent class among these neighbors used as the prediction result. This Euclidean Distance formula is depicted in equation (2) (Riadi et al., 2020). Where, $d(x, y)$ represents the distance variable, $x^i_{training}$ denotes training data, $-y^i_{testing}$ signifies testing data, i denotes the data index, and n indicates the data dimensions.

$$d(x,y) = \sqrt{\sum_{i=1}^{n}\left(x^i_{training} - y^i_{testing}\right)^2} \qquad (2)$$

Confusion Matrix

In the evaluation phase, the confusion matrix serves as a critical tool to evaluate the classification outcomes of the reviewed data. It assesses the accuracy of the classification model in distinguishing between different classes of data (Setiawan, 2020). This matrix facilitates the computation of key evaluation metrics such as accuracy, precision, and recall, using formulas (3), (4), (5), and (6) (Setiawan, 2020). Where, TP represents correctly classified positive instances, FP denotes incorrectly classified positive instances, TN signifies correctly classified negative instances, and FN indicates incorrectly classified negative instances.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \qquad (3)$$

$$Precision = \frac{TP}{TP+FP} \qquad (4)$$

$$Recall = \frac{TP}{TP+FP} \qquad (5)$$

$$F1-Score = 2 * \frac{Precision \times recall}{Precision + recall} \qquad (6)$$

RESULT

Data Crawling

This study successfully collected 3000 comments using the keyword "satire joke", and several hashtags #ormas, #pajak, and #komedi related to satire jokes on the deddy corbuzier channel through the application of crawling techniques. the results of the data collection process carried out by crawling Youtube can be seen in Table 1.

Table. 1 Crawling Data Result

Komentar
Saya petani, kadang miris melihat pejabat foya foya dengan duit negara malah kadang tidak taat pajak.
Setuju sama om Ded dan kawan2. Bukan kuantitas pendidikan yang harus ditambah akan tetapi kualitas pendidikan lah yang harus diperbaiki. Sistem pendidikannya...
Salam dari flores NTT om deddy yang terhormat..kami masih tetap pro bayar pajak..karena kami tau salah satu tanda dari bukti kepemilikan selain atau sebelum terbitnya sertifikat adalah pajak.
Harapan rakyat semoga pajak bisa benar-benar membenahi kualitas pendidikan di negeri ini. Aamiin
Inilah pahlawan tanpa tanja jasa yang sesungguhnya

Text Preprocessing

The first step in processing text is pre-processing, which involves various steps such as removing unnecessary elements from the text, breaking all letters into lowercase, dividing the text into separate words, filtering, and stemming. The process performed during this stage is shown in Table 2.
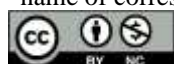
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Table. 2 Preprocessing Step

| Preprocessing Step	Result
Dataset	*Saya petani, kadang miris melihat pejabat foya foya dengan duit negara malah kadang tidak taat pajak.*
Cleaning	*Saya petani kadang miris melihat pejabat foya foya dengan duit negara malah kadang tidak taat pajak*
Case Folding	*saya petani kadang miris melihat pejabat foya foya dengan duit negara malah kadang tidak taat pajak*
Normalization	*['saya', 'petani', 'kadang', 'miris', 'melihat', 'pejabat', 'foya', 'foya', 'dengan', 'duit', 'negara', 'malah', 'kadang', 'tidak', 'taat', 'pajak']*
Stopword	*['saya', 'petani', 'kadang', 'miris', 'melihat', 'pejabat', 'foya', 'foya', 'dengan', 'duit', 'negara', 'malah', 'kadang', 'tidak', 'taat', 'pajak']*
Tokenization	*['saya', 'petani', 'kadang', 'miris', 'melihat', 'pejabat', 'foya', 'foya', 'dengan', 'duit', 'negara', 'malah', 'kadang', 'tidak', 'taat', 'pajak']*
Stemming	*['saya', 'petani', 'kadang', 'miris', 'melihat', 'pejabat', 'foya', 'foya', 'dengan', 'duit', 'negara', 'malah', 'kadang', 'tidak', 'taat', 'pajak']*
Labelling	*saya petani kadang miris melihat pejabat foya foya dengan duit negara malah kadang tidak taat pajak*

Word Weighting

After finishing the labeling of sentiment classes, the next step involves applying Term Frequency-Inverse Document Frequency (TF-IDF) weighting. TF-IDF is used to calculate how frequently a word appears in a document. The TF-IDF calculation is shown in Table 3.

Table. 3 TF-IDF

Word	Weighting (TF-IDF)
saya	0.2309
petani	0.2309
kadang	0.2309
miris	0.4619
melihat	0.2309
pejabat	0.2309
foya	0.4619
dengan	0.2309
duit	0.2309
negara	0.2309
malah	0.2309
tidak	0.2309
taat	0.2309
pajak	0.2309
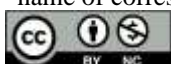
Evaluation

This stage involves evaluating the procedure, which aims to evaluate how effective the model is by measuring accuracy, precision, and accuracy. This is done using the confusion matrix shown in Table 4.

Table. 4 Evaluation

Matrix	NB	K-NN
Accuracy	90.29%	60.75%
Precision	90.32%	72.80%
Recall	90.29%	60.75%
F1 - Score	90.29%	59.16%

To visualize the effectiveness of each algorithm, we employ the Confusion Matrix (CM). Below are examples of the Confusion Matrices for Naive Bayes (NB) and K-Nearest Neighbors (K-NN) algorithms. This aids in gaining a comprehensive insight into their performance, see Figure 2 and Figure 3.
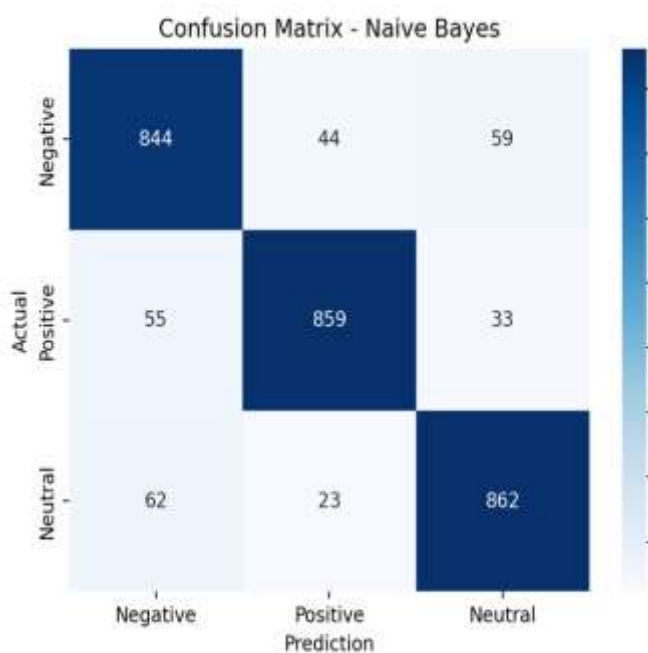

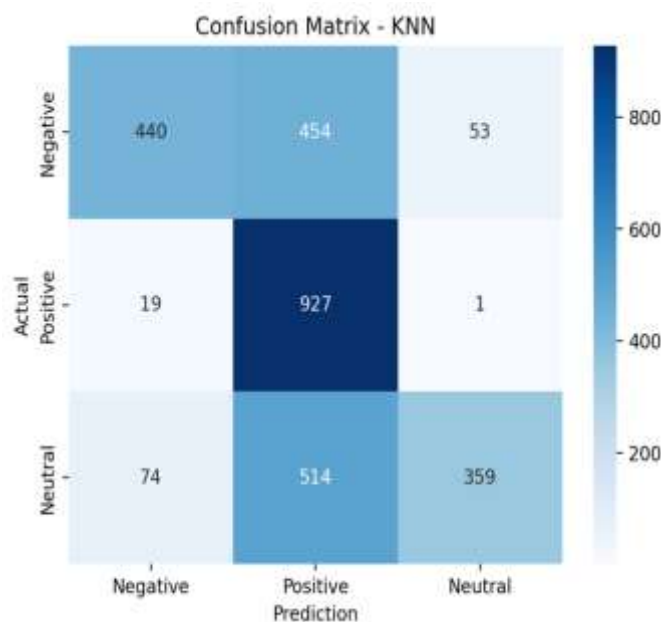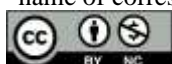Fig. 2 Confusion Matrix Naïve Bayes.   Fig. 3 Confusion Matrix KNN

The performance comparison of Naive Bayes and K-Nearest Neighbors (K-NN) methods is depicted in the bar chart. The diagram shows the performance evaluation of the two methods, Seeing the diagram helps to choose the most suitable method. can be seen in Figure 4.
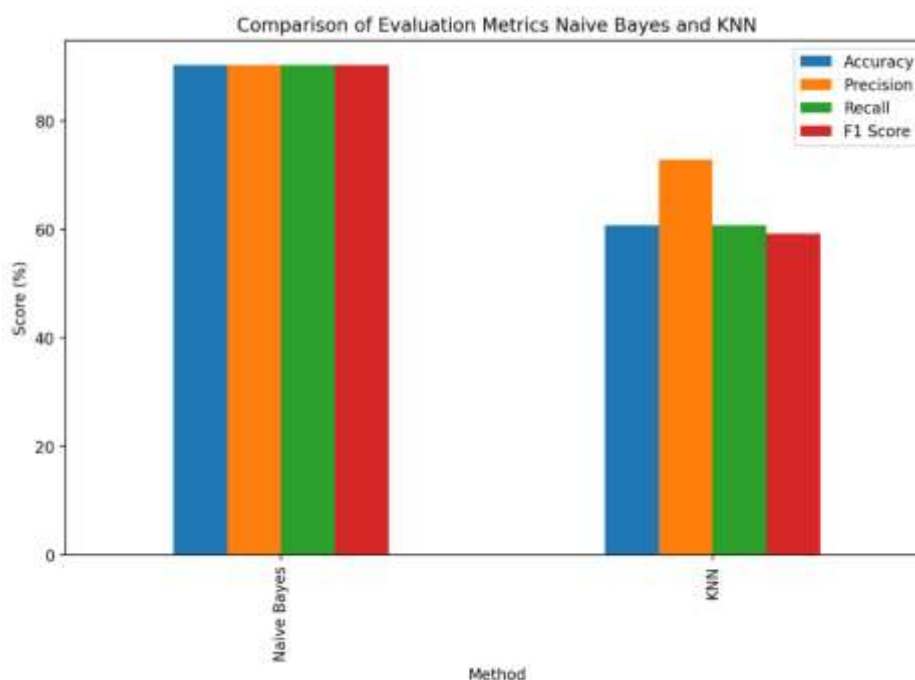
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Fig. 4 Comparison of NB and KNN

DISCUSSIONS

In this discussion section, the findings indicate that the Naive Bayes algorithm outperforms K-Nearest Neighbors in analyzing the sentiment of satire comments on YouTube. This superiority of Naive Bayes could be attributed to its suitability for text data, assuming independence between features, a common scenario in text analysis. On the other hand, K-NN's reliance on distance metrics may be less effective in capturing contextual nuances present in textual data. Naive Bayes demonstrated high accuracy, precision, recall, and F1 score, establishing its reliability for sentiment classification in this study. These outcomes provide a basis for future research in sentiment analysis, exploring alternative methods that may yield more optimal results depending on varying contexts and data characteristics.

CONCLUSION

In this study, from the sentiment analysis of public responses on social media regarding satire jokes using the Naive Bayes and KNN methods, the results show that Naive Bayes has better performance in classifying sentiment. The Naive Bayes method achieved the highest accuracy of 90.29%, while KNN only achieved an accuracy of 60.75%. This shows that Naive Bayes is more effective in identifying and classifying positive, negative, and neutral sentiments towards satire jokes in public responses on social media. This conclusion can serve as a basis for evaluating and improving the understanding of people's responses to satire jokes on the YouTube social media platform.

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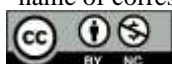
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