JURNAL INFORMATIKA, Vol.12 No.1 April 2025, Page 46-56
ISSN (Print) 2355-6579 | ISSN (Online) 2528-2247
DOI: https://doi.org/10.31294/inf.v12i1.24773

Sentiment Analysis of #Saverafah Hashtag on TikTok Using Naive Bayes and Decision Tree Methods

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Submission:	Revision:	Acceptance:	Available Online:
21-11-2024	12-03-2025	20-03-2025	03-04-2025

Abstract

Social media facilitates user communication, both in positive, negative and neutral aspects. Tiktok is a popular platform that allows users to stay up to date on the latest news, including the major conflict between Palestine and Israel. In this war, many Palestinian civilians, including children and the elderly, became victims, and are currently trying to flee to Rafah to seek protection. The objective of this study is to evaluate public sentiment regarding the news of Palestinian refugees en route to Rafah. To achieve this purpose, we will examine 2982 comments on TikTok relating to the hashtag #SaveRafah, which will be the data to be trained. Prior to classification, the data will undergo a preprocessing process and TF-IDF weighting. The two classification methods will be compared to ascertain the most accurate approach. Because the data at the labeling stage has a larger percentage of positive data 90.7%, this study will employ the technique SMOTE to address class imbalance in the data set. The results showed that the Naive Bayes Multinomial method with the application of SMOTE produced an accuracy of 85.43%, a precision of 86.22%, a recall of 85.43%, and an f1-score of 85.53%. Meanwhile, the Decision Tree C4.5 method with the application of SMOTE produced an accuracy of 94.23%, a precision of 94.58%, a recall of 94.23%, and an f1-score of 94.22%. Based on the evaluation results, the best method for sentiment analysis of the hashtag #SaveRafah is Decision Tree C4.5.

Keywords: Sentiment Analysis, #Saverafah, Tiktok, Naive Bayes, Decision Tree

1. Introduction

The development of the increasingly complex world of technology (Wandri et al., 2024) has led to the emergence of diverse social media platforms that facilitate communication. This social media can be easily accessed via the internet network (Alfiah Zulqornain & Pandu Adikara, 2021). Social media as a form of communication technology has a major impact on attitudes and behavior as well as groups in society. Social media can shape public opinion and perceptions, serving as a powerful instrument for image construction (Habibi et al., 2023). Social media is an online platform enabling individuals to express themselves, interact, collaborate, share, and communicate with others who establish virtual relationships (Kusnadi et al., 2023). Numerous social media platforms exist, including Facebook, Instagram, X, and others. TikTok is a widely utilised application in contemporary society. TikTok is a widely utilised social media platform that provides distinctive and engaging effects, enabling users to effortlessly produce captivating short movies that attract a substantial audience. Nonetheless, the characteristics of this brief video also present constraints. Information communicated in a brief period is often superficial and less thorough. This may lead to a constrained comprehension of the intricate dimensions of a conflict. Although the emotional impact may be substantial, comprehensive analysis is frequently challenging inside the TikTok format. (Andy Satria et al., 2024). TikTok's popularity yields both positive and negative effects, particularly with individual self-image (Aprilyana et al., 2024). TikTok significantly impacts societal communication culture, exemplified by the emergence of a politeness dilemma. This is a significant issue, particularly when the standards of courtesy in communicating on TikTok are breached (Khotimah et al., 2024). TikTok exerts influence in politics through mobilization, utilizing the platform to engage the people, particularly the youth, in political events and protests (Ichwanusafa & Aji, 2024).

The Israel-Palestine conflict is among the most scrutinized international disputes to date. This war has persisted for 75 years, from 1948 until the present (Ramanizar et al., 2021). The conflict between Palestine and Israel has endured for nearly sixty years, historically originating from British governance that commenced in 1917 (Cahya, 2022). Israel persists in the expansion of settlements designated for Jews on Palestinian territory. The Palestinians could only resist to the best of their ability, ultimately resulting in the appropriation of their territory by the Jews. Conversely, Palestinian civilians are compelled to either evacuate or endure the consequences of Israeli governance (Mudore, 2019). The conflict between Palestine and Israel is not solely a theological matter, but also pertains to a humanitarian crisis. The Israeli army has inflicted numerous casualties among Palestinian civilians (Irsyad & Taqwiym, 2021). Numerous countries vehemently condemned the attacks and acts of violence, while others expressed sympathy for one side or the other, or opted for neutrality for both parties (Munandar et al., 2023). Consequently, Palestinian residents sought refuge in the city of Rafah.

Rafah is a city situated near the southern extremity of the Gaza Strip, significant in the historical and geopolitical context of the Palestinian-Israeli conflict. On January 12, 2024, an Israeli bombardment resulted in the deaths of 67 Palestinian inhabitants in Rafah. The Gaza Strip is believed to have a population of approximately 1.5 million Palestinians, a figure that has quintupled since the onset of Israeli attacks on Gaza (Chrismonica, 2024). The attacks by Israel have not only caused loss of life but have also impeded the provision of military supplies to other Palestinian regions. UN authorities stated that the Rafah strike obstructed relief activities essential for sustaining the population across the Gaza Strip. This situation exacerbated the starvation and mortality rates among Palestinian population (Zuhriyah, 2024).

The intensity of this conflict has escalated over several years, culminating in October 2023, with the Israeli assault on the Gaza Strip resulting in over 33,000 fatalities, including several civilians unaffiliated with Hamas (Ramadhan, 2023). The ramifications of this battle extend beyond mere tens or hundreds of casualties; to date, tens of thousands of civilians have been affected by the strife between Palestine and Israel. This confrontation results in casualties, including among civilians, women, and children (Sabiah Vitry et al., 2023). Furthermore, the repercussions of Israel's retaliatory strikes extend beyond human losses, as Israel also targets critical infrastructure, including educational institutions, medical facilities, private property, and residences. The author is highly interested in the current extensively discussed issues.

Based on the background above, the author in this case is motivated to conduct this research which focuses on sentiment analysis based on comments using Tiktok social media. Sentiment analysis involves determining sentiment and classifying the polarity of text in documents or sentences to determine categories such as positive, negative and neutral sentiment (Ardiansyah et al., 2023). There are many benefits of sentiment analysis from a perspective, including being able to obtain a general picture such as public recognition of service quality, monitoring of a product, politics, and investor decisions (Ipmawati et al., 2017). This study analyzed 2982 comment data related to the hashtag #SaveRafah on Tiktok social media using the Naive Bayes and Decision Tree methods. Sentiment analysis on the TikTok platform is vital for comprehending public perspective of the Palestine-Israel conflict, as TikTok is among the most extensively utilized social media for the rapid and direct expression of thoughts. Regulating the dissemination of public opinion across many online venues is a multifaceted issue. Consequently, academics endeavor to leverage comments on TikTok as a valuable information source, given the platform's extensive accessibility and large user base. Researchers aim to extract diverse insights regarding public opinion on specific subjects as evidenced by TikTok comments (Mufidati Nur Edma et al., 2024).

This study has the primary benefit of understanding public opinion regarding the Palestine-Israel conflict through sentiment analysis of TikTok comments, which includes positive, negative, and neutral perceptions, allowing for a quick and effective understanding of public opinion and enriching the literature on sentiment analysis on social media, particularly on humanitarian conflicts. The primary contribution of this study is the use of TikTok comments as a source of public opinion data, using a combination of Naive Bayes and Decision Tree algorithms. This systematic approach not only aids in the exploration of public emotions toward the conflict, but also serves as a methodological reference for future research.

2. Research Methods

Research methods are the phases that researchers undertake to acquire a comprehensive understanding of the study. This study analyzed 2982 comment data related to the hashtag #SaveRafah on Tiktok social media. The stages involved in executing this research approach are shown in Figure 1.

The research stages in Figure 1 are related to various reference articles from (Astuti & Astuti, 2022) and (Ansori & Holle, 2022). From these two publications, the author can develop the stages of this research and determine the research objectives.

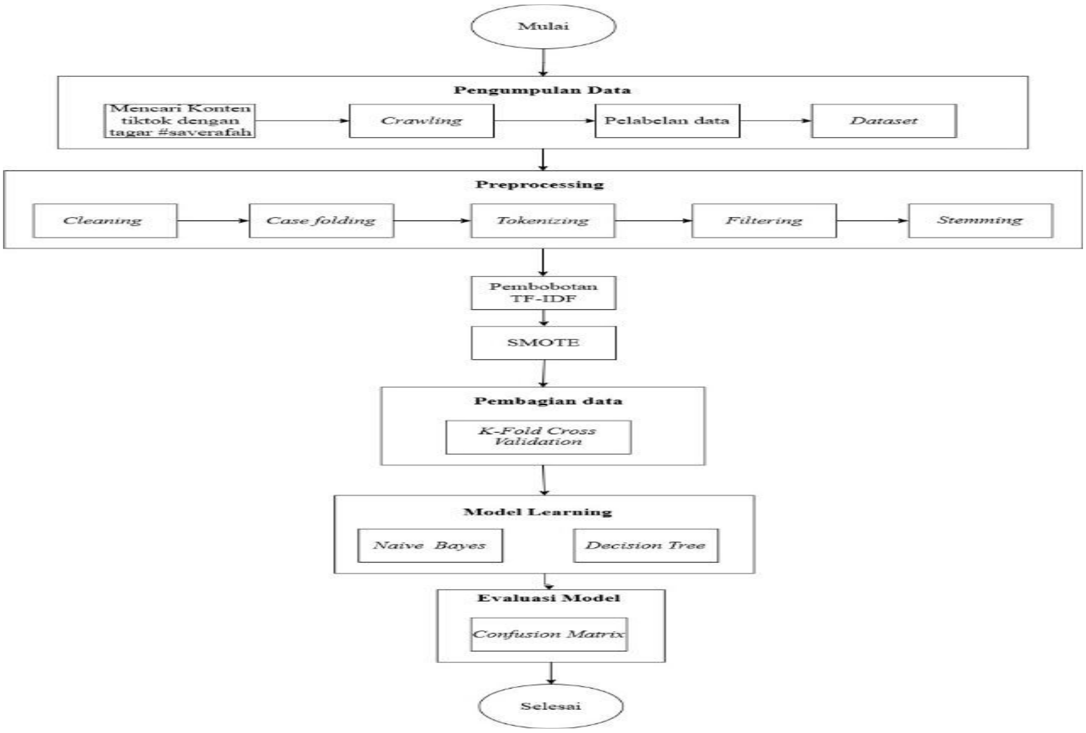


Figure 1. Research stage

1. Data Collection
   At this phase of the investigation, data was gathered using crawling techniques from the TikTok social media platform using the hashtag #saverafah. The data collection method was conducted using crawling techniques using Chromium from the Chrome application. The gathered data is thereafter stored in CSV format to enable additional sentiment analysis.

2. Data Labeling
   At this phase of the research, unsupervised data is transformed into supervised data via the data labelling procedure. This labelling is conducted to ascertain the positive, negative, and neutral classifications that will be recorded in the dataset table by the annotator responsible for providing the label. In this study, the author employed three annotators. This labelling presents the details provided by the three annotators in the subsequent table 1.

Table 1. Annotator Data Labeling Details

Description	Positive	Negative	Neutral	Total
Annotator 1	2704	185	193	2982
Annotator 2	2709	169	104	2982
Annotator 3	2703	173	106	2982
Total	8116	527	403	8.946

This study used the Fleiss kappa equation due to the involvement of three annotators in the labelling process. The Fleiss kappa approach referenced pertains to the study conducted by (Fauzia Putri et al., 2022) titled "Analysis of Twitter User Sentiment Towards PSBB in Jakarta Using the Naïve Bayes Classifier Method." The author cites this research as a reference for the study. The table presents the samples utilised for computing the kappa value.

Table 2. Data Sample for Kappa

Comment Text	Antr1	Antr2	Antr3	F2	F1	F0
Ya allah selamatkanlah para saudara kami di palestina 😭 😭	Positif	Positif	Positif	3	0	0
😭 😭 😭 hanya doa yang kami mampu membantu MU saudara kami	Netral	Netral	Netral	0	3	0
Bismillah merdekakan Palestina Aamiin	Positif	Positif	Netral	2	1	0

From table 2, field F2 denotes the count of annotators who assigned positive labels, field F1 indicates the count of annotators who assigned negative labels, and field F0 represents the count of annotators who assigned neutral labels. To get the value p_{α} and Pe what is needed is the value Pi dan Pj. From the sample data above, the value obtained is Pi from the first data described in the equation:

$$P1 = \frac{1}{3(3-1)} \times (3^2 + 0^2 + 0^2 - 3) = \frac{1}{6} \times 6 = 1$$

$$P2 = \frac{1}{3(3-1)} \times (0^2 + 3^2 + 0^2 - 3) = \frac{1}{6} \times 6 = 1$$

$$P3 = \frac{1}{3(3-1)} \times (2^2 + 1^2 + 0^2 - 3) = \frac{1}{6} \times 2 = 0{,}33$$

$$P4 = \frac{1}{3(3-1)} \times (0^2 + 1^2 + 2^2 - 3) = \frac{1}{6} \times 2 = 0{,}33$$

$$P5 = \frac{1}{3(3-1)} \times (0^2 + 0^2 + 3^2 - 3) = \frac{1}{6} \times 6 = 1$$

Subsequently, compute Pi for the entire dataset to obtain the Pi value as delineated below.

$$Pi = P1 + P2 + P3 + P4 + P5 + \cdots + Pn$$
$$Pi = 1 + 1 + 0{,}33 + 0{,}33 + 1 + \ldots + 1$$
$$Pi = 2965{,}92$$

Based on the data that has been deleted, the remaining data is 2982 data. Then calculate $\boldsymbol{p_0}$ with equation 2.4 so that the calculation is produced as described below.

$$\boldsymbol{p_0} = \frac{1}{2982} \times 2965{,}92 = 0{,}9946076$$

Based on the data obtained, it is known that the number of positive labels is 2704 labels, the number of negative labels is 169 labels and the number of neutral labels is 106 labels. So to get the Pj value for the positive, neutral and negative categories can be obtained with the equations and calculations described as follows.

$$P2 = \frac{1}{2982 \times 3} \times 2704 = 0{,}302258$$

$$P1 = \frac{1}{2982 \times 3} \times 169 = \frac{169}{8946} = 0{,}018891$$

$$P0 = \frac{1}{2982 \times 3} \times 106 = \frac{106}{8946} = 0{,}011849$$

After getting the Pj value in the three categories, the Pe calculation uses the equation:

$$Pe = P_2^2 + P_1^2 + P_0^2$$
$$Pe = 0{,}302258^2 + 0{,}018891^2 + 0{,}011849^2$$
$$Pe = 0{,}0913599 + 0{,}00035687 + 0{,}000140399 = 0{,}0918572$$

After getting the p_0 and Pe values, the kappa calculation uses the following equation:

$$Kappa = \frac{\boldsymbol{p_0 - p_e}}{\boldsymbol{1 - p_e}} = \frac{0{,}9946076 - 0{,}0918572}{1 - 0{,}0918572} = \frac{0{,}9028}{0{,}9082} = 0{,}9940$$

Based on the kappa scale, with a kappa calculation result of 0.9940, the results are included in the Almost perfect agreement category, which means it is very good.

3. Text Preprocessing
   Preprocessing is a crucial phase that facilitates the subsequent step of eliminating or lowering unnecessary features for classification. The input data is unprocessed, ensuring that the outcome of the procedure is a high-quality document intended to facilitate the classification process. The subsequent preprocessing procedure is as follows:
   1). Cleaning is a process implemented to sanitize URLs, punctuation, emojis, numbers, and other components deemed irrelevant (Hanafiah et al., 2023).
   2). Case folding step is essential for converting capital letters in the text to lowercase to ensure consistency (Sholihah et al., 2024).
   3). Tokenizing is the process of separating each component of the data according to the designated space. This stage entails the division of the text in the data into distinct words or tokens (Abror et al., 2024).
   4). Filtering is the stage of removing useless words into basic words and a list of stopwords using Indonesian (Syarifuddinn, 2020).
   5). Stemming is method eliminates the process of converting words into essential words containing Word affixes-suffixes, prefixes, and their combinations (Setiawan & Nastiti, 2024).
4. TF-IDF weighting
   The subsequent phase involves word weighting by computations based on TF-IDF. The TF-IDF method is used to measure the weight or level of importance of a word in a

document or collection of documents (Kusuma & Cahyono, 2023) which combines the frequency of words in the document with the inverse frequency of words in the entire document (Adiyanto & Handayani, 2022), thus giving a higher weight to the words that are used. rarely appears but has important meaning (Muktafin et al., 2020).

5. SMOTE
   SMOTE is a resampling method designed to address imbalances in class distribution with the objective of equalizing class representation (Pramayasa et al., 2023). This study use the Synthetic Minority Oversampling Technique to address class imbalance in the dataset. The SMOTE method will be employed to rectify the imbalance in the current dataset, as the data at the labeling stage exhibits a higher percentage of positive data at 90.7%. By employing the SMOTE technique, the class in the data achieves equilibrium across the three categories of Positive, Negative, and Neutral.
6. Data Sharing
   This study employed K-Fold cross-validation for evaluation testing, according to the following references (Ma'rifah et al., 2020; Soper, 2021; Wardhani & Lhaksmana, 2022) the common choice of k is 10, which yields a reliable estimate of the model's performance.
7. Model
   1) Naive Bayes is a supervised learning classification method, as it relies on human supervisors who manually classify the training data. Moreover, Naive Bayes has a brief classification duration, so accelerating the sentiment analysis system's procedure (Gunawan et al., 2018).
   2) A Decision Tree is an organized framework of attributes intended for evaluation to forecast its outcome. Each internal node exhibits a test on the attribute, with the outcomes of the test represented by the branches, and the class label contained within each node (Cahyaningtyas et al., 2021).
8. Model Evaluation
   Method evaluation is the final stage in this research, focusing on measuring the performance of the naive Bayes and decision tree methods that have been built in the evaluation process carried out using a confusion matrix, which provides an overview of how well the method classifies data.

3. Results and Discussion

3.1. Data Collection

During the data collection phase for this study, the author amassed 2,982 entries from the TikTok social media platform pertaining to the Palestine-Israel conflict under the hashtag #saverafah. The data was obtained using a crawling strategy that employs Chromium from the Google Chrome program, commencing on June 18, 2024.

3.2. Data Labeling

The labeling procedure is conducted collaboratively to guarantee that each data point is accurately labeled in accordance with the established agreement for textual data.

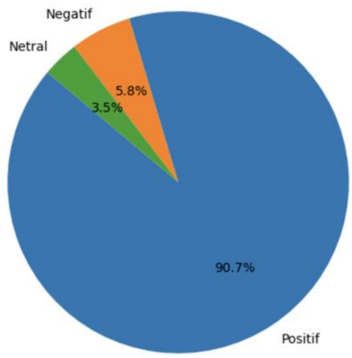


Figure 2. Class pie chart

Figure 2 illustrates the sentiment label distribution in the data, with 90.7% of the data classified as positive, 5.8% of the data is classified as Neutral, only 3.5% is classified as Negative. A kappa calculation was performed to assess the degree of concordance among the three annotators for the sentiment labeling, taking into account the potential for agreement to arise.

Figure 3 presents the kappa calculation results for sentiment categorization by multiple annotators across three categories: Positive, Negative, and Neutral. Each row represents the labeling outcomes for distinct data sets. The Fleiss' Kappa score of 0.9689 signifies a substantial consensus among the annotators, indicating that the labeling is executed proficiently and the results are dependable for subsequent research.

3.3. Text Preprocessing

The preprocessing phase of this research is conducted to prepare the data for sentiment analysis and to develop precise models. The outcomes of this preprocessing enhance data quality, diminish noise, and refine the vocabulary. Preprocessing consists of five stages: cleaning, case folding, tokenization, filtering, and stemming. Text processing is shown in the figure 4.

Figure 4 provides the preprocessing data results. Aimed at enhancing the quality and consistency of the data, each column in the figure reflects a transformation done on the basic data, so more suitable for next investigation.

```
Data Tabulasi:
+------+-----------+-----------+-----------+
|      | Positif   | Negatif   | Netral    |
+======+===========+===========+===========+
|    0 | 3         | 0         | 0         |
+------+-----------+-----------+-----------+
|    1 | 3         | 0         | 0         |
+------+-----------+-----------+-----------+
|    2 | 0         | 0         | 3         |
+------+-----------+-----------+-----------+
|    3 | 2         | 0         | 1         |
+------+-----------+-----------+-----------+
|    0 | ...       | ...       | ...       |
+------+-----------+-----------+-----------+
| 2978 | 0         | 2         | 1         |
+------+-----------+-----------+-----------+
| 2979 | 0         | 3         | 0         |
+------+-----------+-----------+-----------+
| 2980 | 0         | 3         | 0         |
+------+-----------+-----------+-----------+
| 2981 | 3         | 0         | 0         |
+------+-----------+-----------+-----------+

Data sebagai NumPy Array:
[[3 0 0]
 [3 0 0]
 [0 0 3]
 ...
 [0 3 0]
 [0 3 0]
 [3 0 0]]

Fleiss' Kappa: 0.9689
```

Figure 3. Kappa Results

	Data Awal	Cleaning	Case folding	Tokenizing	Filtering	Stemming
0	seandainye itu indonesia, udh pasti di robohka...	seandainye itu indonesia udh pasti di robohkan...	seandainye itu indonesia udh pasti di robohkan...	[seandainye, itu, indonesia, udh, pasti, di, r...	[seandainye, indonesia, udh, robohkan, tembok,...	seandainye indonesia udh roboh tembok tu masya...
1	Ya allah selamatkanlah para saudara kami di pa...	Ya allah selamatkanlah para saudara kami di pa...	ya allah selamatkanlah para saudara kami di pa...	[ya, allah, selamatkanlah, para, saudara, kami...	[ya, allah, selamatkanlah, saudara, palestina]	ya allah selamat saudara palestina
2	😭😭😭 hanya doa yang kami mampu membantu MU saud...	hanya doa yang kami mampu membantu MU saudara ...	hanya doa yang kami mampu membantu mu saudara ...	[hanya, doa, yang, kami, mampu, membantu, mu, ...	[doa, membantu, mu, saudara]	doa bantu mu saudara
3	Bismillah merdekakan Palestina Aamiin	Bismillah merdekakan Palestina Aamiin	bismillah merdekakan palestina aamiin	[bismillah, merdekakan, palestina, aamiin]	[bismillah, merdekakan, palestina, aamiin]	bismillah merdeka palestina aamiin
4	ada yg tau kenapa di penjarain gitu? 😭😄	ada yg tau kenapa di penjarain gitu	ada yg tau kenapa di penjarain gitu	[ada, yg, tau, kenapa, di, penjarain, gitu]	[yg, tau, penjarain, gitu]	yg tau penjarain gitu
...	...	...	...	...	...	...
2977	moga semua dpermudahkan Allah ,,save plastine	moga semua dpermudahkan Allah save plastine	moga semua dpermudahkan allah save plastine	[moga, semua, dpermudahkan, allah, save, plast...	[moga, dpermudahkan, allah, save, plastine]	moga dpermudahkan allah save plastine
2978	ya Allah Mesir kenapa kamu GK mau bantu saudar...	ya Allah Mesir kenapa kamu GK mau bantu saudar...	ya allah mesir kenapa kamu gk mau bantu saudar...	[ya, allah, mesir, kenapa, kamu, gk, mau, bant...	[ya, allah, mesir, gk, bantu, saudara, mu]	ya allah mesir gk bantu saudara mu
2979	miris banget mesir semoga baik aja sodara saya...	miris banget mesir semoga baik aja sodara saya	miris banget mesir semoga baik aja sodara saya	[miris, banget, mesir, semoga, baik, aja, soda...	[miris, banget, mesir, semoga, aja, sodara]	miris banget mesir moga aja sodara
2980	ternyata mesir tidak jauh beda dengan isr4el	ternyata mesir tidak jauh beda dengan isr4el	ternyata mesir tidak jauh beda dengan isr4el	[ternyata, mesir, tidak, jauh, beda, dengan, i...	[mesir, beda, isr4el]	mesir beda isr4el
2981	ya Allah Lindungilah saudara kami yang sedang ...	ya Allah Lindungilah saudara kami yang sedang ...	ya allah lindungilah saudara kami yang sedang ...	[ya, allah, lindungilah, saudara, kami, yang, ...	[ya, allah, lindungilah, saudara, palestina, a...	ya allah lindung saudara palestina aamiin

Figure 4. Preprocessing Results

3.4. TF-IDF weighting

During the TF-IDF phase of this study, the computation of TF-IDF revealed words with corresponding TF-IDF values. The TF-IDF method demonstrates the capacity to evaluate words based on their frequency inside a specific document relative to the full corpus. Consequently, TF-IDF serves as a potent instrument for finding and differentiating keywords in sentiment analysis.

Figure 5 depicts the outcomes of TF-IDF computations for terms in sentiment analysis. Each row displays a word alongside a TF-IDF value that signifies the word's importance. This method aids in identifying pertinent terms, rendering it an effective tool for sentiment analysis.

3.5. SMOTE

During the SMOTE phase, the positive class data is imbalanced relative to other classes, which may subsequently lead to overfitting. The SMOTE approach balances the data across the three classes: Positive, Negative, and Neutral.

	aamiin	aamin	ad	adil	agama	ahli	air	aja	ajaib	akan	...	ya	yaa	yaaa	yaallah	yahudi	yaman	ye	yg	zalim	zaman
0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.152669	0.0	0.0
1	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.287063	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0
2	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0
3	0.381460	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0
4	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.344777	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2977	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0
2978	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.163590	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0
2979	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.532615	0.0	0.0	...	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0
2980	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0
2981	0.627585	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	...	0.277867	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0

Figure 5. TF-IDF Results

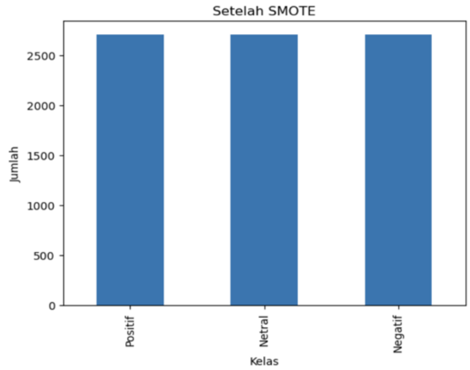


Figure 6. Results After SMOTE

The outcomes of the SMOTE implementation depicted in Figure 6 were conducted to address the issue of data imbalance. Prior to the implementation of SMOTE, the positive class significantly outnumbered the negative and neutral classifications. Utilizing SMOTE balances the data among the three classes, hence enhancing model quality and assuring equitable representation of all classes in the sentiment analysis.

3.6. Performance Evaluation of SMOTE-Free Methods in Sentiment Analysis

1). Naive Bayes

This technique employs 10-fold cross-validation, wherein the dataset is partitioned into two equal segments. Each fold is utilized alternately as training data and testing data.

The confusion matrix in Figure 7 illustrates the performance of the Naive Bayes algorithm in the absence of SMOTE. The classification results are illustrated in this matrix, which displays the predicted labels in the columns and the actual labels in the rows. The model successfully classified 2,681 data as Positive, but there were errors, such as 36 Negative data predicted as Negative and 137 Negative data predicted as Positive. The assessment of the Confusion Matrix yields accuracy, precision, recall, and F1-Score. The subsequent image illustrates these values.

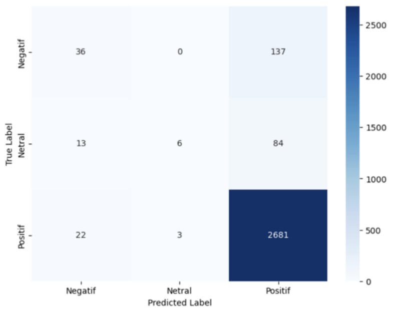


Figure 7. Confusion matrix without SMOTE

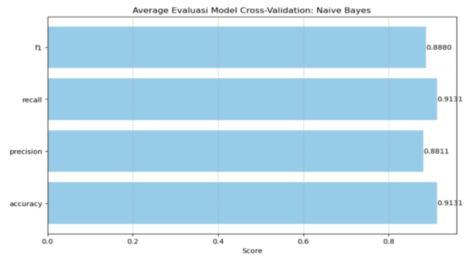


Figure 8. Accuracy, Precision, Recall and F1-Score Results of Naive Bayes without SMOTE in Python

Figure 8 illustrates the outcomes of the Naive Bayes model assessment via cross-validation. The method is capable of classifying TikTok data associated with the hashtag #saverafah, resulting in an average F1 score of 88,80%, an average precision of 88,11%, an average recall of 91,31%, and an average accuracy of 91,31%.

2). Decision Tree

This technique employs 10-fold cross-validation, wherein the dataset is partitioned into two equal segments. Each fold is utilized alternately as training data and testing data.

The confusion matrix in Figure 9 illustrates the performance of the Decision Tree algorithm in the absence of SMOTE. The model successfully classified 2,607 data as Positive, but there were also misclassifications, such as 84 Negative data predicted as Negative and 71 Negative data predicted as Positive. The evaluation of the Confusion Matrix yields accuracy, precision, recall, and F1-Score. The subsequent image illustrates these values.

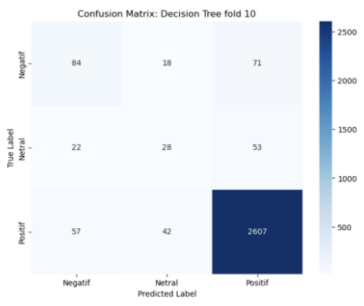


Figure 9. Confusion matrix without SMOTE

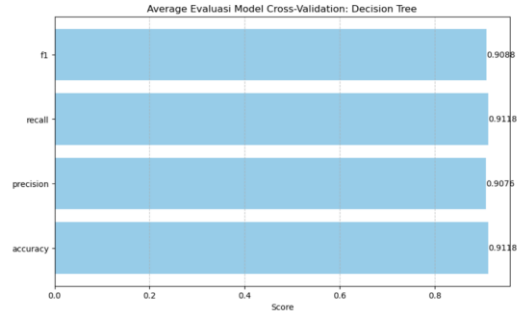


Figure 10. Accuracy, Precision, Recall and F1-Score Results of Decision Tree without SMOTE in Python

Figure 10 illustrates the outcomes of the Decision Tree model assessment via cross-validation. The shown metrics include accuracy at 91.18%, precision at 90.77%, recall at 91.31%, and F1-Score at 90.88%.

3.7. Evaluation of Method Performance with SMOTE Application in Sentiment Analysis

1). Naive Bayes

This technique employs 10-fold cross-validation, wherein the dataset is partitioned into two equal segments. Each fold is utilized alternately as training data and testing data.

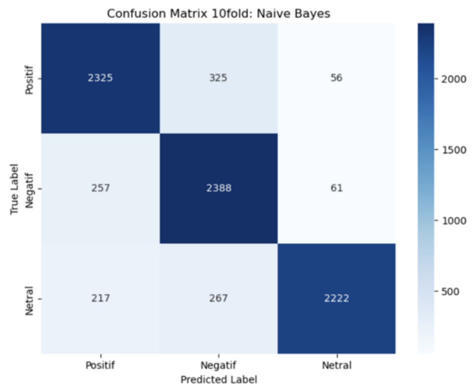


Figure 11. Confusion matrix using SMOTE

Figure 11 shows the confusion matrix showing the performance of the Naive Bayes algorithm in sentiment analysis after applying SMOTE. This matrix illustrates the classification results, where the model successfully classified 3,225 data as Positive, 2,388 data as Negative, and 2,222 data as Neutral. However, there were some misclassifications, such as 325 Positive data predicted as Negative and 56 Positive data predicted as Neutral. The evaluation of the Confusion Matrix yields accuracy, precision, recall, and F1-Score. The subsequent image illustrates these values.

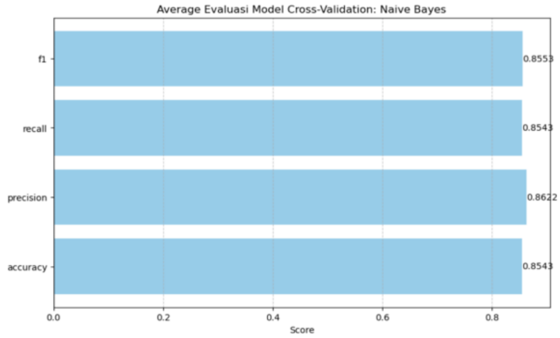


Figure 12. Accuracy, Precision, Recall and F1-Score Results of Naive Bayes with SMOTE in Python

Figure 12 illustrates the outcomes of the Naive Bayes model assessment via cross-validation. The approach can categorize TikTok data associated with the hashtag #saverafah, achieving an average accuracy of 85,43%, an average precision of 86,22%, an average recall of 85,43%, and an average F1 score of 85,53%.

2). Decision Tree

This technique employs 10-fold cross-validation, wherein the dataset is partitioned into two equal segments. Each fold is utilized alternately as training data and testing data.

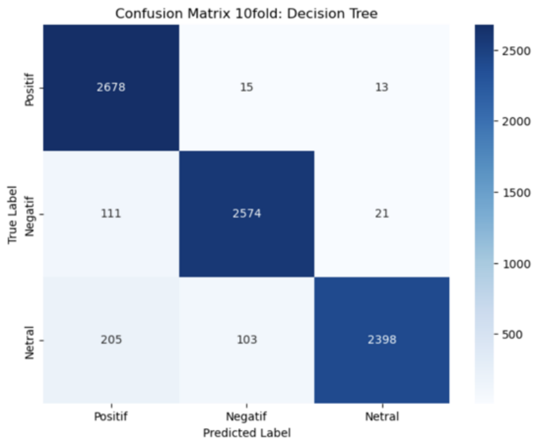


Figure 13. Confusion matrix using SMOTE

Figure 13 shows the confusion matrix showing the performance of the Decision Tree algorithm in sentiment analysis after applying SMOTE. The model successfully classified 2,678 data as Positive, 2,574 as Negative, and 2,398 as Neutral. Although there were some misclassifications, such as 111 Negative data predicted as Positive, these results show good performance of the model. The evaluation of the confusion matrix yields accuracy, precision, recall, and F1-score. The subsequent image illustrates these values.

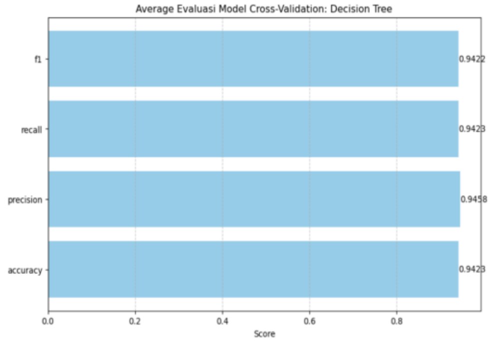


Figure 14. Results of Accuracy, Precision, Recall and F1-Score of Decision Tree with SMOTE in Python

Figure 14 illustrates the outcomes of the Decision Tree model assessment via cross-validation. The shown metrics include accuracy at 94.23%, precision at 94.58%, recall at 94.23%, and F1-Score at 94,22%.

3.8. Model Evaluation Results Analysis

After this evaluation, there were differences between each model in terms of accuracy, precision, recall, and F1-Score.

Table 3. Confusion Matrix Evaluation Results

Method	Average			
	Accuracy	Precision	Recall	F1-Score
Naive Bayes	0,8543	0,8622	0,8543	0,8553
Decision Tree	0,9423	0,9458	0,9423	0,9422

Table 3 shows there are clear differences between Naive Bayes and Decision Tree, with Naive Bayes exhibiting superior precision values. In the Decision Tree technique, the metrics of accuracy, precision, recall, and F1-Score exhibit a more balanced performance with superior accuracy compared to Naive Bayes.

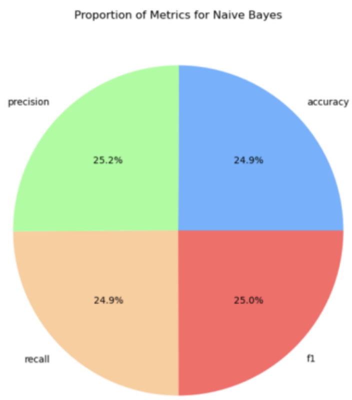


Figure 15. Pie Chart of Evaluation Results with Naive Bayes

Figure 15 shows a pie chart illustrating Naive Bayes displays a confusion matrix evaluation with 24.9% accuracy, 25.2% precision, 24.9% recall, and 25.0% F1-Score.

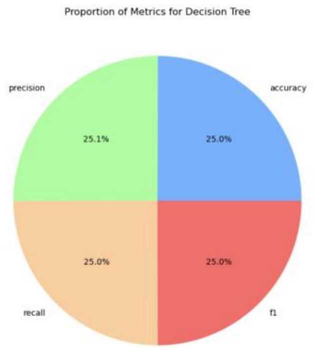
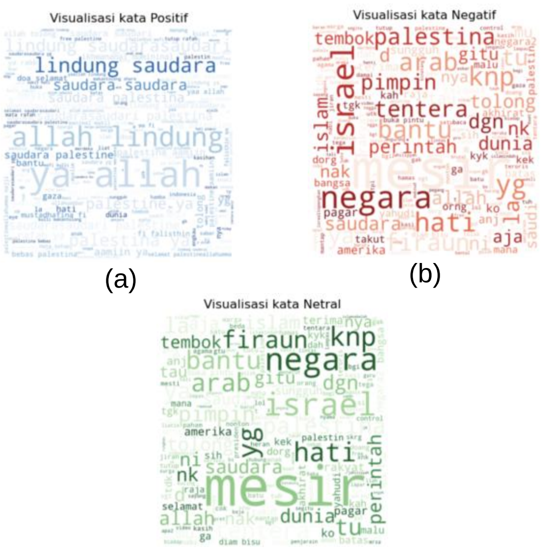


Figure 16. Pie Chart of Evaluation Results with Decision Tree

Figure 16 shows a pie chart illustrating the Decision Tree's evaluation via a confusion matrix, indicating an accuracy of 25.0%, precision of 25.1%, recall of 25.0%, and an F1-Score of 25.0%.

3.9. Visualization

At the visualization stage of this research, it displays words from the dataset that show the emergence of positive, negative and neutral sentiments using word clouds which can be seen in figure 17.



(a) (b)

(c)

Figure 17. (a) Positive Word Visualization, (b) Visualization of Negative Words, (c) Neutral Word Visualization.

The study's results show that most of the comments on TikTok about #SaveRafah are good. This shows that people are emotionally supporting and standing with the Palestinian people. This shows that a lot of people around the world are feeling sorry for the victims. This can change how people in other countries see things and encourage them to help and work for peace. People know TikTok as a place to have fun, but it has also become a place to talk about politics and helping others. Concern generated by hashtags like #SaveRafah can change the way the world works by getting people to donate money and spread the word. These results give the government, groups, and individuals ideas on how to understand public opinion and feelings in order to plan diplomatic actions that will take good feelings into account.

4. Conclusion

The public opinion analysis of the Palestine-Israel conflict can be conducted effectively using a machine learning approach, as evidenced by the sentiment analysis results obtained from remark data on TikTok with the hashtag #Saverafah. Because the data at the labeling step contains a higher percentage of positive data, namely 90.7%, the SMOTE method will be utilized to correct the imbalance in the current data set. The Decision Tree C4.5 method demonstrated superior performance in comparison to the Naive Bayes Multinomial method after the application of SMOTE in the study. The Naive Bayes Multinomial method with SMOTE achieved an accuracy of 0.8543, a precision of 0.8622, a recall of 0.8543, and an F1 score of 0.8553, while the Decision Tree C4.5 method achieved an accuracy of 0.9423, a precision of 0.9458, a recall of 0.9423, and an F1 score of 0.9422. These results suggest that the Decision Tree C4.5 method is more effective in analyzing sentiment on imbalanced data, as it produces more consistent and precise results. Public sentiment toward the Palestine-Israel conflict, as indicated by the hashtag #Saverafah, is generally favorable.

Reference

Abror, N., Novita, R., Mustakim, & Afdal, M. (2024). Sentiment Analysis on the Impact of Artificial Intelligence (AI) Development to Determine Technology Needs. In *Jurnal Sistem Cerdas*.

Adiyanto, A. T., & Handayani, D. (2022). Information Retrieval Sistem Kearsipan Pencarian Dokumen Di Dinas Pemberdayaan Perempuan Dan Perlindungan Anak Kota Semarang Menggunakan Metode Vector Space Model. *Jurnal Mahajana Informasi*, *7*(1).

Alfiah Zulqornain, J., & Pandu Adikara, P. (2021). Analisis Sentimen Tanggapan Masyarakat Aplikasi Tiktok Menggunakan Metode Naïve Bayes dan Categorial Propotional Difference (CPD). *Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *5*(7), 2886–2890. http://j-ptiik.ub.ac.id

Andy Satria, M.Taufiq Kurniawan, Putri Imilia Amanda, & Daniyal Arkan. (2024). Social Media Instagram, Tiktok, dan X Dalam Pengungkapan Pelanggaran Hukum Dalam Konflik Antara Palestina Dan Israel. *Jurnal*

Teknik Informatika Dan Teknologi Informasi, *4*(1), 14–27. https://doi.org/10.55606/jutiti.v4i1.3419

Ansori, Y., & Holle, K. F. H. (2022). Perbandingan Metode Machine Learning dalam Analisis Sentimen Twitter. *Jurnal Sistem Dan Teknologi Informasi (JustIN)*, *10*(4), 429. https://doi.org/10.26418/justin.v10i4.51784

Aprilyana, D. P., Priatna, W., & Setiawati, S. (2024). Implementasi Algoritma Naïve Bayes dan Algoritma C4.5 Untuk Melakukan Analisis Sentimen terhadap Ulasan Komentar Pengguna TikTok di Google Play Store. *Jurnal Pelita Teknologi*, *19*(1), 34–50.

Ardiansyah, D., Saepudin, A., Aryanti, R., & Fitriani, E. (2023). Analisis Sentimen Review Pada Aplikasi Media Sosial Tiktok Menggunakan Algoritma K-NN Dan SVM Berbasis PSO. *Jl. Kramat Raya*, *7*(2).

Astuti, T., & Astuti, Y. (2022). Analisis Sentimen Review Produk Skincare Dengan Naïve Bayes Classifier Berbasis Particle Swarm Optimization (PSO). *Jurnal Media Informatika Budidarma*, *6*(4), 1806. https://doi.org/10.30865/mib.v6i4.4119

Cahya, Ega. N. (2022). Agresi Israel Terhadap Palestina Yang Berujung Pelanggaran Hak Asasi Manusia Pada Palestina. *Jurnal Pendidikan PKN*, *3*(1), 43–56.

Cahyaningtyas, C., Nataliani, Y., & Widiasari, I. R. (2021). Analisis sentimen pada rating aplikasi Shopee menggunakan metode Decision Tree berbasis SMOTE. *AITI: Jurnal Teknologi Informasi*, *18*(Agustus), 173–184.

Chrismonica. (2024, February 19). *Mengenal Kota Rafah: Sejarah, Lokasi, dan Kondisi Sekarang*. Orami. https://www.orami.co.id/magazine/kota-rafah

Fauzia Putri, A., Ernawati, I., & Muliawati, A. (2022). Analisis Sentimen Pengguna Twitter Terhadap PSBB Di Jakarta Menggunakan Metode Naïve Bayes Classifier. In *Seminar Nasional Informatika*.

Gunawan, B., Sasty, H., #2, P., Esyudha, E., & #3, P. (2018). Sistem Analisis Sentimen pada Ulasan Produk Menggunakan Metode Naive Bayes. *JEPIN (Jurnal Edukasi Dan Penelitian Informatika)*, *4*(2), 17–29. www.femaledaily.com

Habibi, M. K., Normansyah, A. D., & Khoerudin, C. M. (2023). Peran Warga Negara Melalui Media Sosial Dalam Membentuk Opini Publik. *Triwikrama: Jurnal Ilmu Sosial*, *4*(12), 1–9.

Hanafiah, A., Haza Nasution, A., Arta, Y., Wandri, R., Nasution, H. O., & Mardafora, J. (2023). Sentiment Analysis Of Customer Reviews Of Shopee Products Based On Wordcloud Using Naïve Bayes Classifier Algorithm. *Journal of Information Technology and Computer Science (INTECOMS)*, *6*(1).

Ichwanusafa, R., & Aji, M. P. (2024). Pengaruh Media Sosial Tiktok Terhadap Tingkat Partisipasi Politik Mahasiswa Generasi Z di UPN Veteran Jakarta. *Pengaruh Media Sosial Tiktok*, *2*(4), 329–337. https://doi.org/10.5281/zenodo.11199238

Ipmawati, joang., kusrini., & taufiq luthfi, emha. (2017). Komparasi Teknik Klasifikasi Teks Mining Pada Analisis Sentimen. *Indonesian Journal on Networking and Security*, *6*(1), 28–36.

Irsyad, H., & Taqwiym, A. (2021). Sentimen Analisis Masyarakat Terhadap Rakyat Palestina dengan Klasifikasi Naive Bayes. *Jurnal Sistem Telekomunikasi Elektronika Sistem Kontrol Power Sistem & Komputer*, *1*(2), 167–176.

Khotimah, Y. N., Nuzulia Armariena, D., & Murniviyanti, L. (2024). Krisis Kesantunan Masyarakat Indonesia dalam Sosial Media Tiktok pada Postingan Kolom Komentar Fujianti Utami: Studi Kasus Pelanggaran Maksim Kesantunan. In *Indonesian Research Journal on Education* (Vol. 4). https://irje.org/index.php/irje

Kusnadi, E., Reni, D., & Annisa, N. (2023). Dampak Media Sosial Tiktok Terhadap Pembentukan Kesadaran Politik Peserta Didik Dalam Berkewarganegaraan. In *AoEJ: Academy of Education Journal* (Vol. 14).

Kusuma, I. H., & Cahyono, N. (2023). Analisis Sentimen Masyarakat Terhadap Penggunaan E-Commerce Menggunakan Algoritma K-Nearest Neighbor. *Jurnal Informatika Jurnal Pengembangan It*, *8*(3), 302–307. https://doi.org/10.30591/jpit.v8i3.5734

Ma'rifah, H., Wibawa, A. P., & Akbar, M. (2020). Klasifikasi Artikel Ilmiah Dengan Berbagai Skenario Preprocessing. *Sains Aplikasi Komputasi Dan Teknologi Informasi*, *2*(2), 70. https://doi.org/10.30872/jsakti.v2i2.2681

Mudore, S. B. (2019). Peran Diplomasi Indonesia Dalam Konflik Israel-Palestina. *Jurnal CMES*, *12*(2), 170–181.

Mufidati Nur Edma, W. N., Andini, E. N., & Widodo, I. (2024). Analisis Sentimen Pada Pengguna Tiktok Menggunakan Metode Random Forest (Studi Kasus: Jessica-Mirna). *Journal Of Social Science Research*, *4*(3), 14477–14489.

Muktafin, E. H., Kusrini, K., & Luthfi, E. T. (2020). Analisis Sentimen Pada Ulasan Pembelian

Produk Di Marketplace Shopee Menggunakan Pendekatan Natural Language Processing. *Eksplora Informatika*, *10*(1), 32–42. https://doi.org/10.30864/eksplora.v10i1.390

Munandar, A., syafaat yaasin, M., Ardian Firdaus, R., & Syarif Hidayatullah Jakarta, U. (2023). Analisis Sentimen Netizen Indonesia Mengenai Boikot Produk. *Tauhidinomics: Journal of Islamic Banking and Economics*, *3*(1), 23–40.

Pramayasa, K., Md, I., Maysanjaya, D., Ayu, G., & Diatri Indradewi, A. (2023). Analisis Sentimen Program Mbkm Pada Media Sosial Twitter Menggunakan KNN Dan SMOTE. *SINTECH Journal*, *2*(6), 89–98. https://doi.org/10.31598

Ramadhan, F. A. (2023). Peran Hukum Internasional dalam Menengahi Konflik Israel-Palestina pada Tahun. *Rio Law Jurnal*, *5*(1), 314–328. https://doi.org/10.36355/.v1i2

Ramanizar, H., Fajri, A., Binsar Sinaga, R., Mubarok, H., Pangestu, A. D., & Prasvita, D. S. (2021). Analisis Sentimen Pengguna Twitter terhadap Konflik antara Palestina dan Israel Menggunakan Metode Naïve Bayesian Classification dan Support Vector Machine. In *Seminar Nasional Mahasiswa Ilmu Komputer dan Aplikasinya (SENAMIKA) Jakarta-Indonesia*.

Sabiah Vitry, H., Ummatin, K., Hasni Azzahra, M., Putri Amanda, A., & Permata Suci, D. (2023). Konflik Israel Dan Palestina "Analisis Manajemen Konflik Yang Mempengaruhi Mental Health Anak Anak Palestina." *Jurnal Multidisiplin Ilmu Sosial* , *2*(2), 2023–2024.

Setiawan, M. J., & Nastiti, V. R. S. (2024). DANA App Sentiment Analysis: Comparison of XGBoost, SVM, and Extra Trees. *Jurnal Sisfokom (Sistem Informasi Dan Komputer)*, *13*(3), 337–345. https://doi.org/10.32736/sisfokom.v13i3.2239

Sholihah, N., Abdulloh, F. F., & Rahardi, M. (2024). Sentiment Analysis on KPU Performance Post-2024 Election via YouTube Comments Using BERT. *Sinkron*, *8*(4), 2222–2232. https://doi.org/10.33395/sinkron.v8i4.14040

Soper, D. S. (2021). Greed Is Good: Rapid Hyperparameter Optimization and Model Selection Using Greedy K-Fold Cross Validation. *Electronics*, *10*(16), 1973. https://doi.org/10.3390/electronics10161973

Syarifuddinn, M. (2020). Analisis Sentimen Opini Publik Terhadap Efek PSBB Pada Twitter Dengan Algoritma Decision Tree, KNN, Dan Naïve Bayes. *INTI Nusa Mandiri*, *15*(1), 87–94. https://doi.org/10.33480/inti.v15i1.1433

Wandri, R., Setiawan, P. R., Arta, Y., & Hanafiah, A. (2024). Designing a Learning Game for Elementary School Students in Learning Mathematics using a Mobile Platform. *Jurnal Sistem Informasi*, *13*(3), 1139–1146. http://sistemasi.ftik.unisi.ac.id

Wardhani, F. H., & Lhaksmana, K. M. (2022). Predicting Employee Attrition Using Logistic Regression With Feature Selection. *Sinkron*, *7*(4), 2214–2222. https://doi.org/10.33395/sinkron.v7i4.11783

Zuhriyah, U. (2024, May 8). *Kenapa Israel Serang Rafah dan Bagaimana Kondisi Palestina Kini?* Tirto. https://tirto.id/kenapa-israel-menyerang-rafah-dan-kondisi-palestina-kini-gYt1