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Sentiment Analysis on Kanzler's "Hacks Aburamen Bakso Hot" Campaign on Tiktok

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ABSTRACT: This study investigates the sentiment analysis of Kanzler's "Hacks Aburamen Bakso Hot" campaign on TikTok, a platform increasingly significant in digital marketing. The research explores how viral marketing and influencer-driven strategies impact consumer attitudes. Sentiment analysis was conducted on comments from five TikTok videos using natural language processing techniques, including data preprocessing, TF-IDF weighting, and Naïve Bayes classification. Results reveal predominantly positive sentiments, indicating the campaign's success in enhancing brand perception and engagement. These findings highlight the efficacy of influencer marketing in leveraging social media for product promotion and provide actionable insights for future digital marketing strategies.

KEYWORDS: sentiment analysis, influencer marketing, tiktok campaign, naive bayes, rapid miner.

I. INTRODUCTION

This research discusses the sentiment analysis of the Kanzler "Hacks Aburamen Bakso Hot" campaign on TikTok. It is crucial to study this campaign to observe the development of marketing strategies alongside technological advancements and societal trends. With the rapid technological growth, access to information has become increasingly easy and fast, influencing public attitudes. People must adapt quickly to technological changes to avoid falling behind (Rohman, et al., 2024). As consumer behavior changes in the digital era, marketers have begun shifting their strategies to digital marketing, a trend accelerated by the COVID-19 pandemic, which significantly increased internet access. Companies must adapt, master technology, innovate, and collaborate to dominate future markets. Utilizing data-driven marketing and creating relevant content are also strategies for facing consumer market challenges in the digital era (Riofita, et al., 2024).

Social media is one of the most widely used platforms for information-seeking. In 2024, Indonesia had 139 million social media users, with platforms like WhatsApp, Instagram, Facebook, TikTok, and Telegram being the most popular. Indonesia ranks second globally for TikTok ad exposure, reaching a total audience of 126 million people (We Are Social, 2024). This rapid growth of TikTok in Indonesia is an interesting phenomenon to study. TikTok, originating from China, was established in 2018 and gained significant traction, reaching 100 million users and 1 billion daily video views (Khasanah, 2024). TikTok entered Indonesia in 2018 as a short-video platform and has evolved into social commerce with key features like live shopping. This transformation has made TikTok popular due to its focus on content creation, allowing anyone to be featured on the For You Page (FYP).

TikTok has become a promising marketing platform for industries in Indonesia, ranging from beauty and culinary to fashion and electronics. The use of TikTok can influence culinary business owner profitability, because with TikTok Culinary industry owner has effectively utilized TikTok for product marketing, achieving greater visibility and audience reach. Influencers play a significant role in this marketing strategy. Influencers, known for their expertise in specific fields, have the ability to be heard and recognized by the public (Nandy, n.d.). Using influencers on social media is a form of electronic word-of-mouth (eWOM), an evolution of traditional word-of-mouth marketing. Brands commonly use influencer marketing to enhance brand awareness.

In recent years, numerous food hacks and recipes have gone viral on TikTok, such as egg sandwiches and cheese balls (Sari, 2020). Kanzler, an established processed food brand since 1999, has capitalized on this trend by promoting hacks and recipes featuring their products, including sausages, chicken nuggets, and meatballs in various flavors (Kanzler, 2022). Kanzler often collaborates with influencers to promote their recipes, such as Ramen Hacks featuring Kanzler Bakso Hot, Nugget Chili Salt Hacks, Sosis Shake Hacks, and Aburamen Bakso Hot Hacks. Other known Hacks are Mie Gacoan brand, where they have Mie Gacoan Carbonara Hacks, where influencers make tips to create a special Mie Gacoan with milk, to create Mie Gacoan Carbonara Hacks.

This study focuses on the sentiment analysis of the "Hacks Aburamen Bakso Hot" campaign, where influencers demonstrated how to create spicy broth ramen with Kanzler Singles Bakso Hot as a topping. Kanzler hired influencers to create Hacks with spicy sauce ramen with Kanzler Singles Bakso Hot as a topping (Shadirafirdausi, n.d.) . The study aims to evaluate the effectiveness of Kanzler's viral marketing efforts in promoting their Singles Bakso Hot product. This research also examines whether exposure to the campaign changes public attitudes towards the brand. Consumer attitudes towards a brand are influenced by satisfaction, experience, and trust in the product. These attitudes can shift due to experiences with the product, word-of-mouth, and media exposure (Schiffman and Wisenbilt, 2014).

This research analyzes comments on five TikTok videos from the "Hacks Aburamen Bakso Hot" campaign, selected based on the highest number of comments from influencers on TikTok. Researchers will use sentiment analysis by the comments on selected TikTok influencers. Sentiment analysis is a knowledge that is used to measure public opinion on media based on literature on comment (Ikhsani dan Abdulloh, 2023). Sentiment analysis will be conducted to categorize the sentiments expressed in these comments as positive, negative, or neutral.

Sentiment analysis, a branch of natural language processing (NLP), identifies and categorizes emotions expressed in written text. It is a valuable tool for understanding public opinions about a topic, product, or service (Ikhsani and Abdulloh, 2023). This study employs the Naïve Bayes Classifier, a probabilistic data mining algorithm that classifies data based on probability and statistics, as outlined by Thomas Bayes (Ramadhani and Suryono, 2024).

While prior research on Kanzler has primarily focused on the impact of influencer marketing on purchase intention, this study highlights sentiment analysis to provide insights into the success of the "Hacks Aburamen Bakso Hot" campaign. These findings are expected to benefit Kanzler and other culinary brands in refining their social media marketing strategies.

II. LITERATURE REVIEW

A. Influencer Marketing

Influencer marketing is a digital marketing strategy where individuals and brands collaborate to promote products or services through the influencer's social media platforms. This collaboration leverages popular social media users to enhance a company's marketing campaigns (Ozuem & Willis, 2022, p. 211). The key distinction between influencer marketing and traditional marketing lies in the emotional and personal connections that marketers and influencers can establish with social media users (Peng, 2023).

A survey conducted by Sprout Pulse on influencer marketing revealed that 80% of marketers agreed influencers are essential to overall social media strategies (Sprout Social, 2024). Previous studies have also found that social media influencers significantly impact positive brand perception (Sijabat et al., 2022, p. 12). This influence is due to the substantial follower base of influencers and their ability to shape the perceptions and even behaviors of their audiences (Armana & Kusumasari, 2024; Ozuem & Willis, 2022; Porral et al., 2021; Thamrin & Utami, 2023).

An influencer's reputation is often built through their activities and content on social media, enabling them to engage more effectively with followers who share similar interests (Peng, 2023). Influencers typically possess distinct personalities, content styles, and target markets, which makes them attractive collaborators for companies seeking to build trust and increase brand awareness among influencer followers. Additionally, influencers help businesses enhance their credibility and brand reputation.

Kanzler has implemented a comprehensive influencer marketing strategy on TikTok, collaborating with influencers at various levels, including nano, micro, mid-tier, macro, and mega influencers. Thamrin & Utami (2023) reported that respondents are more likely to purchase food products due to influencer content on social media than traditional advertisements or promotions. Thus, influencers' opinions have a significant impact on respondents' purchasing decisions. Porral et al. (2021) further emphasized that the effectiveness of influencer endorsements is not only influenced by attributes such as trustworthiness, expertise, and appeal but also by the alignment between the influencer and the product.

In their quantitative study, Armana & Kusumasari (2024) evaluated how Kanzler builds brand awareness and consumer trust by optimizing influencer marketing to promote products and motivate influencer audiences to make purchases. Their findings showed that Kanzler's influencer marketing efforts significantly affect consumer loyalty. By using influencers as promotional media, Kanzler ensures its message reaches the target audience directly while reducing larger promotional costs, such as those associated with television commercials (Gogali et al., 2022).

This study focuses on influencer content promoting Kanzler's "Hacks Aburamen Bakso Hot" campaign on TikTok. Using the hashtag #AburamenSoHot, the research team will filter and select the top five videos with the highest number of comments. Subsequently, netizens' sentiments will be analyzed based on the comment sections of these influencer videos.

B. Sentiment Analysis

Sentiment analysis is a branch of natural language processing (NLP) that focuses on the automatic identification and categorization of emotions and sentiments expressed in written text (Tan et al., 2023). This technique is invaluable for companies or individuals to gather information and make decisions based on public opinions, thoughts, and impressions about a topic, product, service, or subject (Nip & Berthelier, 2024; Wankhade et al., 2022). Sentiment can be understood as the feelings underlying positive or negative opinions expressed or as emotions implied in neutral opinions (Nip & Berthelier, 2024; Shanmugavadivel, 2022).

According to Aftab et al. (2023), sentiment analysis has a wide range of applications across various fields, including:

Customer Insights:

Sentiment analysis enables companies to gain customer insights into attitudes, perceptions, and sentiments regarding their products or brands. This provides a deeper understanding of customer needs, preferences, and challenges, forming the basis for data-driven decision-making.

Brand Management :
Machine learning techniques facilitated by sentiment mining empower businesses to understand consumer sentiment towards their brand and customer expectations. This understanding helps companies proactively address negative consumer sentiments and develop more targeted branding strategies by identifying factors that drive consumer emotions and the success or failure of products or services.

Decision-Making and Strategy Development:
Sentiment analysis provides consumer feedback and sentiment data, enabling companies to make informed decisions and dvelop strategies for product improvement, marketing, customer engagement, and more.
Zahra (2024) highlights that social media is the most significant source of sentiment data compared to other online media, such as podcasts, blogs, forums, and official websites. Responses from TikTok and YouTube influencers often generate positive sentiment and popular mentions, demonstrating influencers' significant impact on monitoring product innovation.
In the context of this study, the research team will analyze feedback from audiences on TikTok influencer videos promoting Kanzler's "Hacks Aburamen Bakso Hot" campaign. Comments from these videos will be classified into positive, negative, and neutral sentiments, providing insights into the audience's perspective on the campaign.

III. METHODOLOGY

This study comprises several stages, including data collection, text processing, implementation of the Naive Bayes algorithm, and testing. These stages are illustrated in the following diagram:

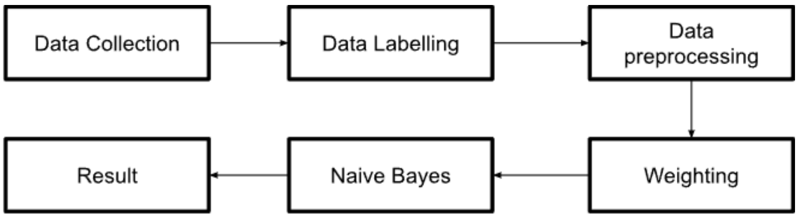

Figure 1 Sentiment Analysis Processes

1. Data Collection

Data collection is the process of obtaining the dataset (Kurnia et al., 2024). In this study, data collection involves extracting comments from five influencer videos on TikTok using the hashtag #AburamenSoHot, focusing on the five videos with the highest number of comments. These comments are downloaded using a Google Chrome browser plugin called TTCommentExporter, which facilitates users in extracting and saving comments from a TikTok video in CSV or Excel format.

2. Data Labeling

The next step is data labeling, which is carried out manually by the researchers. The data will be categorized into three sentiment classes: positive, negative, and neutral. As there are three researchers involved in this study, the final label will be determined based on majority voting. For instance, if two researchers classify a comment as positive and one classifies it as negative, the final label for that comment will be positive.

3. Data Preprocessing

In this stage, the labeled data will be cleaned to create a more structured dataset. The data cleaning process will be conducted using RapidMiner software and will involve several steps, including:
Cleansing: Removing noise such as usernames, emoticons, and punctuation marks, which are irrelevant for the analysis (Lestari & Nurisusilawati, 2024).
Case Folding: Converting uppercase letters into lowercase, which is essential for subsequent stages (Arsi et al., 2021).
Tokenizing: Splitting the text into individual words to facilitate the stopword removal and stemming processes (Lestari & Nurisusilawati, 2024).
Stopword Removal: Eliminating words that do not carry meaningful relevance to the research, such as conjunctions, prepositions, and pronouns. This step reduces system workload by focusing only on essential words (Irsyad et al., 2024).
Stemming: Converting inflected words into their base forms to standardize the dataset (Kurnia et al., 2024).

4. Weighting

After data collection, labeling, and preprocessing, the next step is weighting the data. Data weighting assigns scores to each word within a document (Gunawan et al., 2018). This study employs the TF-IDF (Term Frequency-Inverse Document Frequency) method. Term frequency focuses on terms that frequently appear in the data, while inverse document frequency assigns lower weights to commonly occurring terms (Gunawan et al., 2018).

5. Naive Bayes

The Naive Bayes classification algorithm will be used in this study. Naive Bayes is a probabilistic classifier based on Bayes' Theorem, with a strong (naive) independence assumption (Apriani & Gustian, 2019). This classification method is applied to categorize data into positive, negative, or neutral sentiment (Lestari & Nurisusilawati, 2024).

6. Research Results

After completing the above stages, the study will yield results analyzing the sentiment of the "Hacks Aburamen Bakso Hot" campaign on TikTok. The analysis will determine whether the sentiment trends are predominantly positive, negative, or neutral.

IV. FINDINGS AND DISCUSSION

To process comments from five TikTok videos of the Kanzler "Hacks Aburamen Bakso Hot" campaign, the researchers utilized RapidMiner software. The initial step involved crawling data from each video, followed by a data cleansing stage. This process cleaned the data by removing emoticons, symbols, mentions, and hashtags.

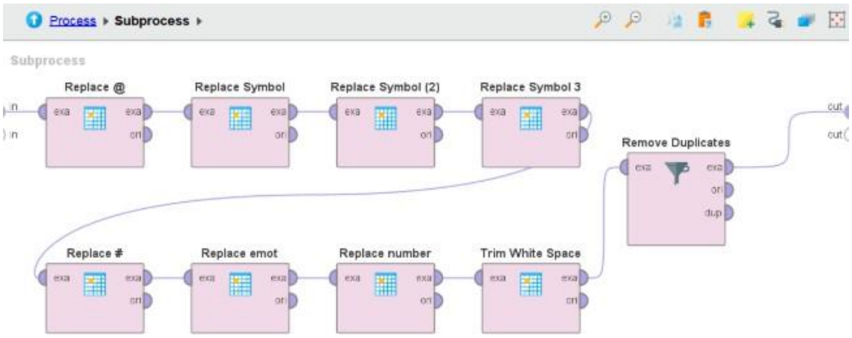

Figure 2 Cleaning Data Process

Next, the cleaned data was processed in RapidMiner to generate a word cloud. The word cloud visually represented the frequency of specific words, highlighting terms that appeared frequently or rarely.

Figure 3 TF-IDF Process (Word Cloud)

At the algorithm stage, researchers manually labeled 70% of the total data as training data. The remaining 30% of the comments were left unlabeled to serve as testing data. Using the Naïve Bayes algorithm, RapidMiner processed the training data to classify sentiments in the testing data. This machine learning approach enabled the algorithm to learn from the training data and predict the sentiment of the testing data.

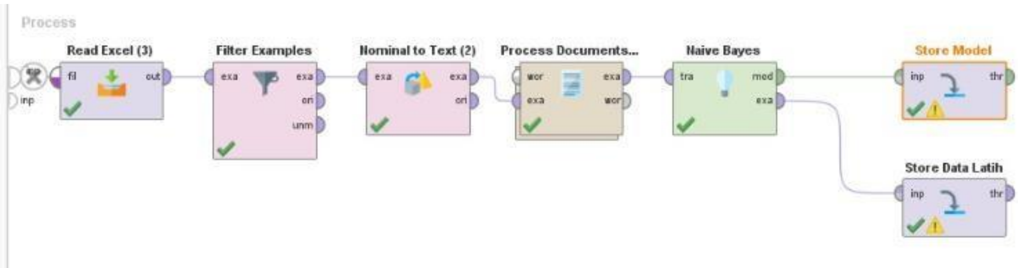

Figure 4 Algorithm Process

In the prediction stage, RapidMiner predicted the sentiment of the 30% testing data based on the training data analysis. Researchers could review and validate the sentiment predictions made for the testing data.

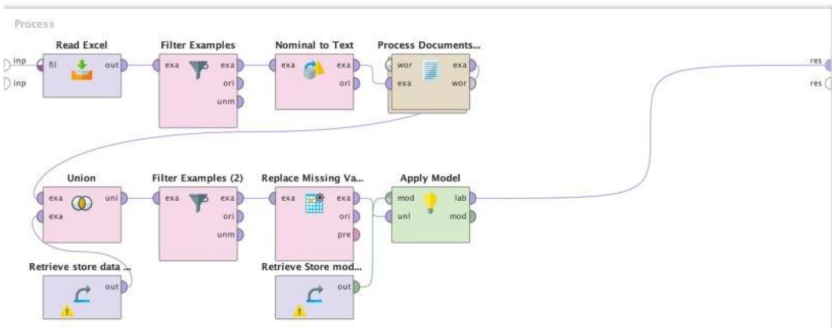

Figure 5 Prediction Process

Finally, during the performance stage, RapidMiner provided a performance report that included the following metrics:
True Positive, True Negative, True Neutral: The actual sentiment labels of the testing data.
Prediction Positive, Prediction Negative, Prediction Neutral: The sentiment predictions generated by the model.
Precision: The proportion of correct predictions for a specific class out of all predictions made for that class.
Class Recall: The proportion of actual data in a class that was correctly identified by the model.

These stages ensured a structured and systematic approach to analyzing sentiment data, providing insights into the effectiveness of the "Hacks Aburamen Bakso Hot" campaign and the accuracy of the machine learning model.

A. Sentiment Analysis Results for Video 1 by Deasty Kartika *(https://vt.tiktok.com/ZS6jvRYUv/)*

The performance analysis of the sentiment classification model for comments on Video 1 shows the following results:

accuracy: 93.47%

	true Positif	true Negatif	true Netral	class precision
pred. Positif	93	0	0	100.00%
pred. Negatif	5	36	3	81.82%
pred. Netral	5	0	57	91.94%
class recall	90.29%	100.00%	95.00%	

Figure 6 Sentiment Analysis Results of Deasty Kartika

The model demonstrates a high overall accuracy, correctly classifying 93.47% of the test data into the sentiment categories of positive, negative, and neutral.

Positive Sentiment

The model effectively recognizes positive sentiment, with a precision of 100% and a recall of 90.29%. Perfect precision indicates that all data predicted as positive sentiment were indeed positive, without any classification errors. However, the slightly lower recall shows that 10% of positive data were not well recognized by the model and were classified as neutral or negative sentiments. This indicates an opportunity to improve the model's sensitivity to positive sentiment through additional training data or algorithm optimization.

Negative Sentiment

The model also performs well in recognizing negative sentiment. Recall reaches 100%, meaning all negative sentiment data were successfully identified by the model. Precision for negative sentiment stands at 81.82%, indicating that 18.18% of negative predictions were actually from other sentiments (neutral). This suggests some misclassification, likely due to similarities in vocabulary or context between negative and neutral sentiments.

Neutral Sentiment

The model's performance in recognizing neutral sentiment is also good, with a precision of 91.94% and a recall of 95%. Most neutral sentiment data were correctly identified, with only a few misclassifications. Errors mainly occurred when neutral sentiment data were classified as negative. This shows the model generally understands the context of neutral data but has room for improvement in minimizing errors for this class.
Based on the class-level analysis, the model performs very well in recognizing positive and neutral sentiments, achieving precision scores above 90%. However, for negative sentiment, while recall is perfect, lower precision suggests the need for re-evaluating training data to reduce misclassification.
With an overall accuracy of 93.47%, the model is considered reliable for sentiment analysis. However, there is still room for improvement in reducing classification errors between sentiment categories.

B. Sentiment Analysis Results for Video 2 by HeyChandra (*https://vt.tiktok.com/ZS6jvbqxK/*)

accuracy: 90.00%

	true netral	true positif	true negatif	class precision
pred. netral	51	0	0	100.00%
pred. positif	4	16	0	80.00%
pred. negatif	7	0	32	82.05%
class recall	82.26%	100.00%	100.00%	

Figure 7 Sentiment Analysis Results of HeyChandra

Overall, the model achieved a high accuracy rate of 90%. This indicates that the majority of test data were correctly classified into their respective sentiment categories, as explained below:

Neutral Sentiment
For the neutral sentiment class, the model correctly classified 51 data points out of a total of 62 actual neutral data points (true neutral). This is reflected in a recall value of 82.26%, indicating that approximately 17.74% of neutral sentiment data were misclassified, most of which were categorized as negative. Nevertheless, the precision for this class reached 100%, indicating that all predictions classified as neutral were entirely consistent with their actual labels.

Positive Sentiment
The model demonstrated excellent performance in the positive sentiment class, with precision and recall values of 80% and 100%, respectively. Out of a total of 16 positive sentiment data points, all were correctly classified. However, there were 4 incorrect positive predictions originating from actual neutral data. Despite this, the performance of this class remains highly satisfactory, as no positive data were missed by the model.

Negative Sentiment
Similar to positive sentiment, the model performed very well in the negative sentiment class, achieving a recall value of 100% and a precision of 82.05%. The model accurately classified all 32 negative data points without any being miscategorized into other classes. However, 7 neutral data points were incorrectly classified as negative, slightly reducing the precision for this class.

C. Sentiment Analysis Results for Video 3 by Itsfrydays (*https://vt.tiktok.com/ZS6jvHped/*)

accuracy: 96.58%

	true negatif	true netral	true positif	class precision
pred. negatif	7	3	1	63.64%
pred. netral	0	38	0	100.00%
pred. positif	0	0	68	100.00%
class recall	100.00%	92.68%	98.55%	

Figure 8 Sentiment Analysis Results of Itsfrydays

Overall, the model achieved a high accuracy rate of 96.58%, indicating that 96.58% of the total test data were correctly classified into sentiment categories (positive, negative, neutral).

Negative Sentiment
The model achieved a recall of 100% for negative sentiment, meaning that all data with negative sentiment were successfully identified by the model. However, the precision was only 63.64%, indicating that approximately 36.36% of negative predictions actually belonged to other sentiments, primarily neutral. This suggests that while the model performs well in detecting negative sentiment, it still struggles to distinguish between negative and neutral sentiments. These errors could be attributed to contextual similarities or overlapping words in the test data.

Neutral Sentiment
For neutral sentiment, the model exhibited excellent performance with a precision of 100% and a recall of 92.68%. All neutral sentiment predictions originated from actual neutral data, but approximately 7.32% of neutral data were misclassified as negative. These results indicate that the model is highly reliable in recognizing neutral sentiment, although there is room for improvement in addressing some misclassifications, which could be refined through further analysis.

Positive Sentiment
The model demonstrated outstanding performance in recognizing positive sentiment, with both precision and recall values of

100% and 98.55%, respectively. Only 1.45% of positive data were misclassified as negative. This high performance in the positive sentiment class highlights the model's strong ability to detect positive sentiment patterns in the test data, reflecting its success in accurately interpreting positive sentiment features

D. Sentiment Analysis Results for Video 4 by Daddy Kuliner (*https://vt.tiktok.com/ZS6jv5PPH/*)

accuracy: 82.61%

	true negatif	true netral	true positif	class precision
pred. negatif	3	1	3	42.86%
pred. netral	0	11	0	100.00%
pred. positif	0	0	5	100.00%
class recall	100.00%	91.67%	62.50%	

Figure 9 Sentiment Analysis Results of Daddy Kuliner

Overall, the model achieved a reasonably high accuracy of 82.61%, indicating that the majority of test data were correctly classified into their respective sentiment categories, as detailed below:

Negative Sentiment
For the negative sentiment class, the model successfully classified all true negative data with a recall of 100%. However, the precision for this class was only 42.86%. This low precision was caused by misclassifications, where the model incorrectly categorized data from the neutral (1 instance) and positive (3 instances) sentiment categories as negative. The low precision indicates that the model struggled to distinguish negative sentiment from other categories. This suggests a similarity in text features that led to misclassification, highlighting the need for data enrichment or feature optimization to improve precision.

Neutral Sentiment
The model demonstrated excellent performance for the neutral sentiment class, with a recall of 91.67% and a precision of 100%. Out of 12 truly neutral data points, 11 were correctly classified, while 1 neutral instance was misclassified as negative. The high precision indicates that all neutral sentiment predictions were fully aligned with their actual labels. However, the recall error of 8.33% suggests room for improving the model's sensitivity to neutral sentiment data.

Positive Sentiment
The model also performed well in the positive sentiment class, achieving a precision of 100%, meaning that all positive sentiment predictions matched their actual labels. However, the recall for this class was only 62.5%, as 3 instances of true positive data were misclassified as negative. This result indicates that the model is less sensitive to positive sentiment data. Efforts to improve the distribution of positive data during model training could enhance recall and overall performance for this sentiment class.

E. Sentiment Analysis Results for Video 5 by Alex (*https://vt.tiktok.com/ZS6jvxGUG/*)

accuracy: 96.46%

	true positif	true negatif	true netral	class precision
pred. positif	22	2	0	91.67%
pred. negatif	0	52	0	100.00%
pred. netral	0	2	35	94.59%
class recall	100.00%	92.86%	100.00%	

Figure 10 Sentiment Analysis Results of Alex

Overall, the model demonstrated a relatively high accuracy of approximately 96.46%, indicating that the data were correctly classified into positive, negative, and neutral sentiment categories, as detailed below:

Neutral Sentiment
The model performed exceptionally well in predicting neutral sentiment, achieving a recall of 94.59% and a precision of 100%. However, there were some errors in prediction, as two negative data points were classified as neutral. This indicates that the model's ability to distinguish neutral data from positive and negative data is highly accurate.

Negative Sentiment
For negative sentiment, the model showed excellent performance with a precision of 100%, meaning all negative predictions were correct. The recall for this class was 92.86%, indicating that approximately four data points that should have been classified as negative were not identified correctly and were misclassified into other categories.

Positive Sentiment

In the positive sentiment category, the model achieved a precision of 91.67% and a recall of 100%, demonstrating that all positive sentiment data were correctly classified. However, the precision result indicates that two negative data points were misclassified as positive. This suggests that while the model effectively identifies all positive data, there is a minor issue in distinguishing positive data from other classes.

V. CONCLUSIONS

This study aimed to analyze the sentiment of the Kanzler Aburamen Bakso Hot campaign on the TikTok platform. Kanzler utilized well-known Key Opinion Leaders (KOLs) to create video hacks featuring recipes made with Kanzler Bakso Hot products. Sentiment analysis on TikTok was conducted using the RapidMiner application, with data from TikTok comments exported via the TTExporter application. Overall, the sentiment of comments on the Kanzler Hacks Aburamen Bakso Hot campaign videos on TikTok tended to be positive. This conclusion is supported by the following points:

Model Performance for Positive Sentiment:

Positive sentiment achieved a relatively high recall rate across most of the videos analyzed, with nearly all positive sentiments being correctly identified by the model. The recall for positive sentiment reached nearly 100% in some cases. The precision for positive sentiment was also notably high, ranging between 91.67% and 100%. This indicates that comments predicted as positive sentiment were indeed correctly classified as such.

Misclassification of Other Sentiments:

In some videos, there were minor errors in classifying neutral or negative sentiments as positive sentiment. However, it can be concluded that the overall context of the comments tended to be positive. While there were some weaknesses in identifying negative and neutral sentiments, positive sentiment remained dominant and exhibited high consistency.

Dominance of Positive Sentiment in the Videos:

The campaign videos demonstrated a strong dominance of positive sentiment in the comments across all videos, with very few negative comments observed. Notably, in videos 3 and 5, almost all positive sentiments were accurately detected and identified by the model.

This study underscores the effectiveness of the campaign in generating a predominantly positive sentiment on TikTok, showcasing the success of the content in engaging its audience.

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