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Travel Content Evaluation through Sentiment and Toxicity Analysis using CRISP-DM

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Abstract−This research, framed by the CRISP-DM methodology, offers a comprehensive analysis of sentiment and toxicity in digital content, focusing on tourism-related videos. Utilizing advanced machine learning models like VADER and TextBlob for sentiment analysis, as well as APIs such as Detoxify and Perspective for toxicity assessment, the study analyzed 25,361 posts, with 23,292 processed for sentiment and 24,171 for toxicity. Various algorithms, including k-NN, DT, NBC, and SVM, were applied with SMOTE to address data imbalance. The SVM algorithm achieved the highest performance with an accuracy of 54.80% and an F-measure of 66.01%, while others showed lower efficacy. The deployment phase integrated these models for real-time analysis, providing actionable insights into user engagement. Findings emphasize the significant impact of sentiments on brand perception and the necessity of managing toxic behavior for a healthier online environment. Despite limitations such as dataset imbalance and model dependency, the study offers valuable recommendations for content creators, advocating for robust moderation and sentiment-based strategies to enhance user interaction. Future research should include diverse datasets and advanced tools to improve the findings' robustness and applicability. This research contributes to understanding digital content dynamics and provides strategic insights for optimizing content creation and user engagement.

Keywords: CRISP-DM; Digital Content; Sentiment; Travel Content; Toxicity

1. INTRODUCTION

Travel review content is a crucial reference for tourists planning trips, offering insights into attractive destinations and highlighting regulations and security systems at these locations. These reviews provide essential support by detailing a destination's appealing aspects and the practicalities related to traveler safety and local laws [1]. Integrating this comprehensive information aids tourists in making informed decisions, enhancing the overall travel experience [2]–[4]. This dual focus on travel content underscores the importance of awareness in ensuring a safe and enjoyable journey [5]–[7]. Consequently, well-rounded travel reviews play a pivotal role in the tourism industry by bridging the gap between leisure and safety considerations.

Audio-visual content reviewing travel destinations captures public attention by delineating permissible activities and the prevailing security systems of the host country. This form of media offers substantial support by vividly portraying the attractions and the regulatory landscape, ensuring travelers are well-informed about local customs and legal boundaries [8]–[11]. Such comprehensive content fosters a heightened awareness among tourists, promoting enjoyment and compliance with local regulations [12], [13], [13]–[15]. Consequently, audio-visual travel reviews significantly contribute to safer and more informed tourism experiences, bridging the gap between exploration and adherence to safety protocols.

This study evaluates the travel content produced by a creator in Egypt, specifically examining a YouTube video titled "Egypt Travel Nightmare. Why I'll Never Go Back." with the ID 8LzuZrkEY18. The video emphasizes the complexities of regulations in Egypt, portraying them as challenging for content creators. This portrayal has significantly captured public interest, amassing 58,309 comments and 9,920,269 views since its release on April 9, 2022. Such engagement suggests that the difficulties highlighted resonate with a broad audience, potentially impacting perceptions of Egypt as a travel destination. Ultimately, the video's widespread response underscores the power of social media in shaping travel narratives and influencing public opinion.

This phenomenon indicates digital content engagement between content creators and viewers on the YouTube platform, implying that negative destination reviews will elicit user comments and boost content statistics. Interaction is evidenced by the high volume of user comments and views, reflecting a robust engagement level driven by contentious or critical content [16]–[19]. Such engagement amplifies the video's reach and stimulates further discussions among viewers [20]–[22]. Consequently, negative reviews paradoxically enhance the visibility and popularity of the content, underscoring the dynamic nature of digital media interactions.

This study analyzes toxicity and sentiment based on viewer comments on published video content using the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology. The analysis involves systematically collecting and processing data to identify patterns and sentiments within the comments, providing insights into viewer reactions and the overall impact of the content [23], [24]. Employing the CRISP-DM framework ensures a structured and comprehensive approach to data mining, facilitating accurate and actionable findings [25]. Ultimately, this research highlights the importance of understanding viewer sentiment and toxicity to manage better and respond to audience engagement in digital content.

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The urgency of this research lies in its potential to address critical gaps in understanding digital content interactions and societal impacts. The study analyzes toxicity and sentiment in viewer comments and provides valuable insights into online engagement dynamics and digital media's influence on public opinion [26]–[29]. Such analysis is crucial in an era where social media significantly shapes perceptions and behaviors, making it imperative to develop strategies for managing negative interactions [30], [30], [31]. Therefore, this research is essential for fostering healthier online environments and enhancing the effectiveness of digital content in engaging audiences constructively.

This research's theoretical and practical contributions are manifold, offering academic and real-world applications. Theoretically, it advances the understanding of digital content interaction by elucidating the mechanisms through which toxicity and sentiment influence online engagement [32]. Practically, the study equips content creators and platform managers with data-driven insights to enhance strategies for fostering positive interactions and mitigating negative ones [32]. This dual contribution underscores the research's significance in bridging the gap between academic theory and practical implementation, ultimately fostering a more informed and constructive digital media landscape.

Similar research in the field has explored various aspects of digital content interactions, mainly focusing on user engagement, sentiment analysis, and the impact of online reviews on public perception. Such studies have provided foundational insights into how digital media influences audience behavior and sentiment [32], [33]. However, this study is limited by its reliance on a single platform and a specific type of content, which may not fully capture the diversity of online interactions across different media and contexts. This limitation suggests the need for broader, multi-platform analyses to enhance the generalizability of the findings, thereby providing a more comprehensive understanding of digital content dynamics.

2. RESEARCH METHODOLOGY

2.1 Gap Analysis

The importance of gap analysis in this research lies in its ability to identify and address existing deficiencies in the current understanding of digital content interactions. The study highlights critical areas requiring further investigation by systematically evaluating the discrepancies between theoretical knowledge and practical applications. This approach informs the development of more effective digital engagement strategies and contributes to refining academic theories related to online behavior. Consequently, gap analysis is crucial for advancing scholarly research and practical methodologies, ensuring a more robust and comprehensive exploration of digital media dynamics.

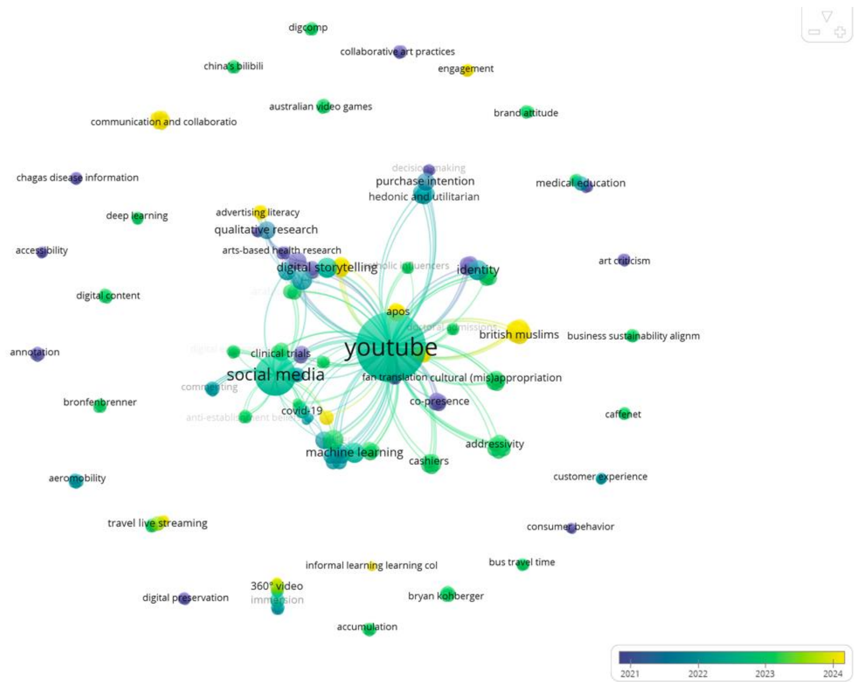

Figure 1. Overlay Visualization of Digital Content Topics (VosViewer)

Figure 1 shows the overlay visualization of digital content topics. Based on the gap analysis results, it is evident that the study of digital content remains expansive and requires further examination through case studies that illustrate the contextuality and novelty of this research's findings. This analysis reveals substantial areas of unexplored potential, highlighting the need for focused investigations that reflect specific situational dynamics. Such case-based approaches provide deeper insights into the unique characteristics and emerging trends in digital content. Therefore, addressing

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these gaps is essential for advancing the field and ensuring that research remains relevant and adaptable to the rapidly evolving digital landscape.

Therefore, this research offers both theoretical and practical contributions. Theoretically, it enriches the academic discourse by providing new insights into the complexities of digital content interactions and user behavior. Practically, the findings equip content creators and digital marketers with actionable strategies to enhance engagement and mitigate negative responses. This dual contribution underscores the study's significance, bridging the gap between theory and practice. Ultimately, the research advances understanding and application in the field, fostering more effective and informed approaches to managing digital content.

2.2 Cross-Industry Standard Process for Data Mining (CRISP-DM)

The framework employed in data processing is the Cross-Industry Standard Process for Data Mining (CRISP-DM). This methodology ensures a structured approach encompassing six phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. By following these phases, the framework facilitates a comprehensive analysis, allowing for the identification of patterns and insights within complex data sets. Using CRISP-DM enhances the reliability and validity of the findings, making it a robust tool for data mining. Consequently, this systematic approach underpins the research's analytical rigor and contributes to its overall credibility.

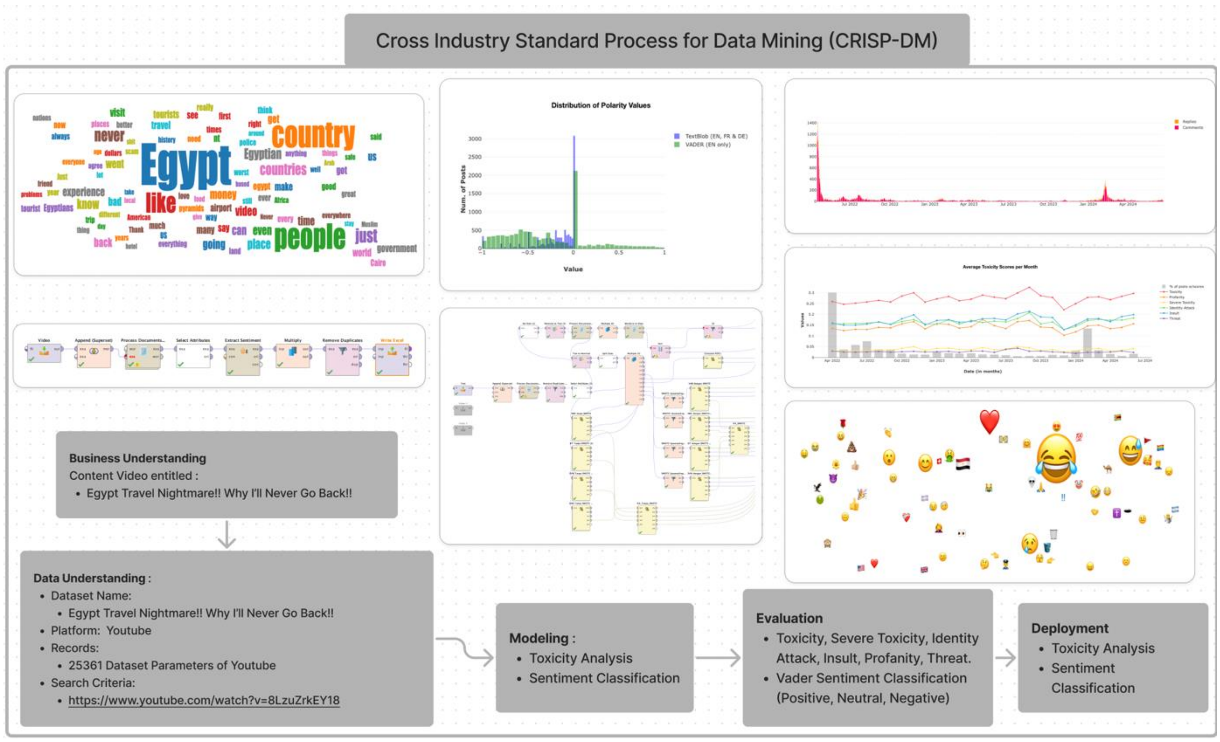

Figure 2. CRISP-DM Framework

Figure 2 shows the CRISP-DM framework. The advantages of CRISPR-DM lie in its structured and iterative approach to data mining. This framework's systematic methodology ensures comprehensive coverage of all phases, from business understanding to deployment, facilitating a thorough and detailed analysis. Its flexibility allows adaptation to various industries and data types, enhancing its applicability and effectiveness. By providing clear guidelines and best practices, CRISP-DM improves the efficiency and reliability of data mining projects. Consequently, the framework's robust structure and adaptability make it an invaluable tool for extracting meaningful insights from complex data sets.

The limitations of CRISP-DM include its potential rigidity and the significant time investment required for thorough implementation. The structured nature of the framework, while beneficial for ensuring a systematic approach, sometimes constrains the flexibility needed for more dynamic or unconventional data mining projects. Additionally, the comprehensive phases outlined in CRISP-DM demand substantial resources and time, which may not always be feasible for all organizations. These constraints suggest that while CRISP-DM offers a robust methodology, it may not suit every context. Therefore, careful consideration is needed to determine its applicability to specific projects and settings.

2.2.1 Business Understanding

The Business Understanding stage of CRISP-DM is critical as it lays the foundation for the entire data mining process. This phase comprehensively defines the project objectives and requirements from a business perspective, ensuring

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alignment with organizational goals. It also includes identifying key business questions that the data mining project aims to address. This clarity helps formulate a relevant and actionable data mining problem. By thoroughly understanding the business context, the process ensures that the subsequent data mining efforts are effectively targeted and deliver meaningful and impactful results. Therefore, this stage is essential for guiding the project towards achieving its intended business outcomes.

In the context of this research, the Business Understanding stage of CRISP-DM focuses on the analysis of travel content published on the YouTube platform with the ID 8LzuZrkEY18, which has garnered 58,309 comments and 9,920,269 views since its publication on April 9, 2022. This stage involves defining the research objectives based on the significant engagement metrics of the video, ensuring the study aligns with the broader goal of understanding digital content interaction. The research aims to uncover insights into the dynamics of viewer behavior by identifying key questions related to user responses and engagement patterns. Consequently, this stage is crucial for guiding the research toward meaningful and actionable findings reflecting the context of high-engagement travel content on YouTube.

Based on the context of the video, it is evident that 2022 represents the post-COVID-19 period during which the tourism sector experienced significant impacts. This period saw the industry grappling with the repercussions of prolonged travel restrictions and reduced international mobility. The challenges faced by the tourism sector were unprecedented, requiring innovative strategies for recovery and adaptation. The video's engagement metrics highlight the heightened public interest in travel content during this recovery phase. Consequently, understanding the dynamics of this period is crucial for formulating effective measures to support the sector's resurgence and resilience.

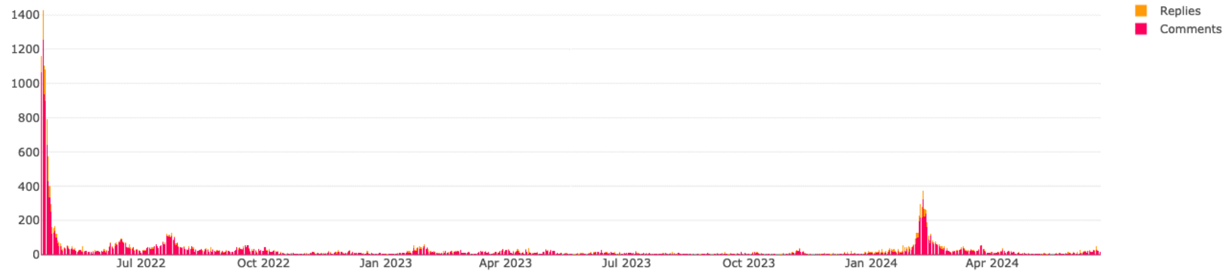

Figure 3. Post-per-day Statistic of the Video (Communalytic)

Figure 3 shows the content's post-per-day statistics. The post-per-day statistics provide insights into the volume of comments on a video published in 2022, which continued to receive substantial engagement in 2024. Notably, the data shows significant interaction on specific dates: June 21 (14 comments), June 20 (22 comments), June 19 (23 comments), June 18 (28 comments), June 17 (21 comments), June 16 (27 comments), June 15 (14 comments), June 14 (18 comments), June 13 (22 comments), and June 12 (25 comments). These figures indicate a sustained interest and high responsiveness among viewers, suggesting the video's content remains relevant and compelling over time. The continued engagement underscores the dynamic nature of digital content interaction, highlighting the importance of understanding temporal trends in audience behavior.

This phenomenon demonstrates that content published in previous years has the potential to gain popularity in subsequent years. The enduring engagement with such content suggests that digital media have a prolonged impact, retaining relevance and attracting new audiences. This pattern indicates that high-quality content, regardless of its initial release date, experiences a resurgence in popularity as it continues to resonate with viewers. Consequently, understanding the factors contributing to digital content's sustained appeal is crucial for maximizing its long-term impact and success in the ever-evolving digital landscape.

Figure 4. Top Ten Poster (Communalytic)

Figure 4 shows the top ten posters. The top ten poster data reveals that several channels actively commented on the video: @Whoareyou-dt4kg (489 comments), @user-hc5po6ym2k (238 comments), @adelrezk5168 (128 comments), @originalthoth7313 (70 comments), @BlackWingedSeraphX (69 comments), @bluetorpido5929 (44 comments), @Houria__Al_Anazi (39 comments), @dollarisinsanicus (36 comments), @tamermustafa5739 (34 comments), and @Abdelrahman76674 (31 comments). This active engagement from multiple users highlights the video's significant impact and reach within the platform. The substantial number of comments from these top

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contributors indicates a high level of interaction and interest, underscoring the video's ability to provoke discussion and maintain viewer engagement over time. This engagement trend emphasizes the importance of understanding user behavior and interaction patterns to enhance content strategy and maximize audience reach.

Consequently, the process advances to the data understanding stage to facilitate comprehension of the types and characteristics of the data that need to be cleaned and further processed. This stage is crucial as it involves initial data exploration, identifying anomalies, missing values, or inconsistencies. Understanding the nature and structure of the data aids in determining the appropriate preprocessing techniques required for accurate analysis. Thus, thorough data understanding ensures that the subsequent data preparation and modeling stages are based on reliable and well-organized data, ultimately enhancing the validity of the research findings.

2.2.2 Data Understanding

The Data Understanding stage of CRISP-DM is fundamental for gaining insights into the data's nature and structure. This phase involves collecting initial data, familiarizing it with its content, and identifying quality issues affecting subsequent analyses. By thoroughly examining the data, it becomes possible to detect patterns, spot anomalies, and determine relationships within the dataset. This understanding is essential for guiding the data preparation and modeling phases, ensuring the data is clean and suitable for analysis. Ultimately, a comprehensive data understanding forms the foundation for accurate and reliable data mining results, significantly enhancing the overall effectiveness of the project.

This research identifies frequently used words to analyze the most common terms appearing in viewer comments on the video. This analysis involves extracting and quantifying the occurrences of specific words to discern prevalent themes and sentiments expressed by the audience. The study aims to uncover underlying patterns and insights into viewer engagement and reactions by focusing on these frequently used words. This approach is instrumental in understanding the collective response to the content, providing a nuanced view of audience perceptions. Consequently, the findings contribute to a deeper comprehension of viewer behavior and content impact.

Figure 5. Frequently Used Words (Communalytic)

Figure 5 shows the frequently used words. The data on frequently used words reveals key terms and occurrences in viewer comments about the video: "Egypt" (374), "country" (226), "people" (216), "like" (163), "just" (103), "never" (94), "countries" (82), "Egyptian" (72), "know" (68), "place" (65), "going" (64), "money" (61), "even" (60), "video" (59), "can" (59), "time" (58), "back" (58), "experience" (58), and "went" (54). These frequent words highlight themes and sentiments, such as the emphasis on Egypt and its people and reactions to the video content. The recurrence of terms related to travel experiences and emotions suggests a strong engagement with the video's subject matter. Consequently, this analysis provides valuable insights into the focal points of viewer interest and the overall impact of the content, underscoring the video's relevance and resonance with its audience.

Figure 6. Emoji Cloud (Communalytic)

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Figure 6 shows the emoji clouds. The emoji cloud data reveals the frequency of various emojis used in viewer comments: 😂 (38), 😅 (20), 🖤 (15), 😢 (12), EG (9), 😊 (9), 😮 (7), 🤮 (4), 💩 (4), 🤣 (4), 👍 (4), 💵 (3), 🎉 (2), 💀 (2), 😍 (2), 🤔 (2), 🐪 (2), 🥰 (2), and 🤷‍♀️ (2). These emojis indicate a range of emotional responses, from amusement and laughter to love, sadness, and surprise. The prominent use of the laughing emoji 😂 suggests that viewers found the content humorous or entertaining, while the Egyptian flag emoji EG highlights the video's cultural context. This diverse emoji usage provides insights into the varied reactions and sentiments of the audience. Consequently, analyzing these emojis helps understand the emotional engagement and the overall reception of the video, offering a nuanced view of viewer interactions.

The impact of emojis and comments on destination branding is significant, influencing public perception and engagement. Emojis, by conveying emotions succinctly, amplify the sentiments expressed in comments, whether positive or negative, thereby shaping the overall tone of the discussion. This emotional layer enhances the visibility and relatability of the content, making it more engaging for a broader audience. Consequently, the aggregation of these emotional cues either bolsters or undermines the brand image of the destination, depending on the prevalent sentiments. Thus, understanding and managing these digital interactions is crucial for maintaining a favorable destination brand and fostering positive audience engagement.

2.2.3 Modeling

The Modeling stage of the CRISP-DM framework is pivotal in transforming prepared data into actionable insights. This phase involves selecting appropriate modeling techniques and algorithms tailored to the specific objectives and data characteristics. Training and testing these models ensures they accurately predict or classify outcomes based on the data inputs. The choice of model and its parameters are crucial, as they directly impact the validity and reliability of the results. Therefore, meticulous attention to model selection and validation is essential for achieving robust and meaningful analytical outcomes, ultimately guiding informed decision-making.

In this research context, modeling is conducted using Communalytic and RapidMiner for comparative analysis. Both tools offer distinct methodologies and algorithms, enabling a comprehensive evaluation of data patterns and insights. By leveraging these platforms, the study identifies which approach yields more accurate and reliable results for the specific dataset. The comparative analysis highlights the strengths and weaknesses of each tool and ensures a robust and nuanced understanding of the data. Consequently, this dual-tool approach enhances the validity of the findings and provides a solid foundation for informed conclusions.

In calculating the toxicity score in Communalytic, 24,171 posts out of 25,361 were processed using the Perspective API. Meanwhile, sentiment analysis was conducted on 23,292 out of 25,361 posts using Vader and TextBlob. These processing methodologies allow for a thorough data evaluation, ensuring that most posts are analyzed for comprehensive insights. Advanced tools like Perspective API, Vader, and TextBlob ensure accurate and reliable results, providing a nuanced understanding of toxicity and sentiment within the dataset. Consequently, this approach enhances the robustness of the findings, facilitating informed conclusions about online discourse.

As a comparison, the data extraction process for reviews in RapidMiner was configured using the Vader model, resulting in score strings for 7,514 out of 9,687 posts. This configuration demonstrates the efficiency and effectiveness of RapidMiner in handling large datasets and generating sentiment scores. The substantial number of processed posts indicates high accuracy and reliability in the sentiment analysis conducted by Vader. Consequently, this comparative analysis underscores the robustness of RapidMiner's capabilities in extracting and analyzing data, providing a solid basis for evaluating the sentiment of the reviews.

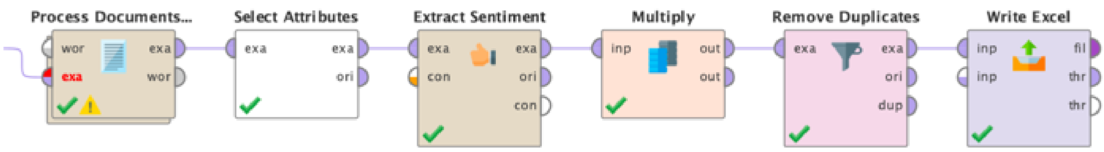

Figure 7. Extract Sentiment (Rapidminer)

Figure 7 shows the extract sentiment process. Using the Extract Sentiment operator in RapidMiner, based on the Vader model, offers significant benefits for sentiment analysis. This operator efficiently processes large volumes of text data, providing accurate sentiment scores that reflect the polarity and intensity of the expressed sentiments. The Vader model's ability to handle nuances in natural language, including slang and emoticons, enhances the robustness and reliability of the analysis. Consequently, applying this operator in RapidMiner facilitates a comprehensive understanding of public sentiment, enabling more informed decision-making and strategic planning based on the extracted insights.

After data extraction, score strings with a value of 0.0 are interpreted as neutral and will be excluded from the analysis. Consequently, only negative and positive values (binominal) are used as labels for further analysis based on the performance of k-NN, SVM, DT, and NBC algorithms. The algorithm demonstrating the best performance will be discussed and analyzed in greater depth within this study. This approach ensures a focused examination of the most effective algorithm, providing valuable insights into its application and efficacy in sentiment analysis.

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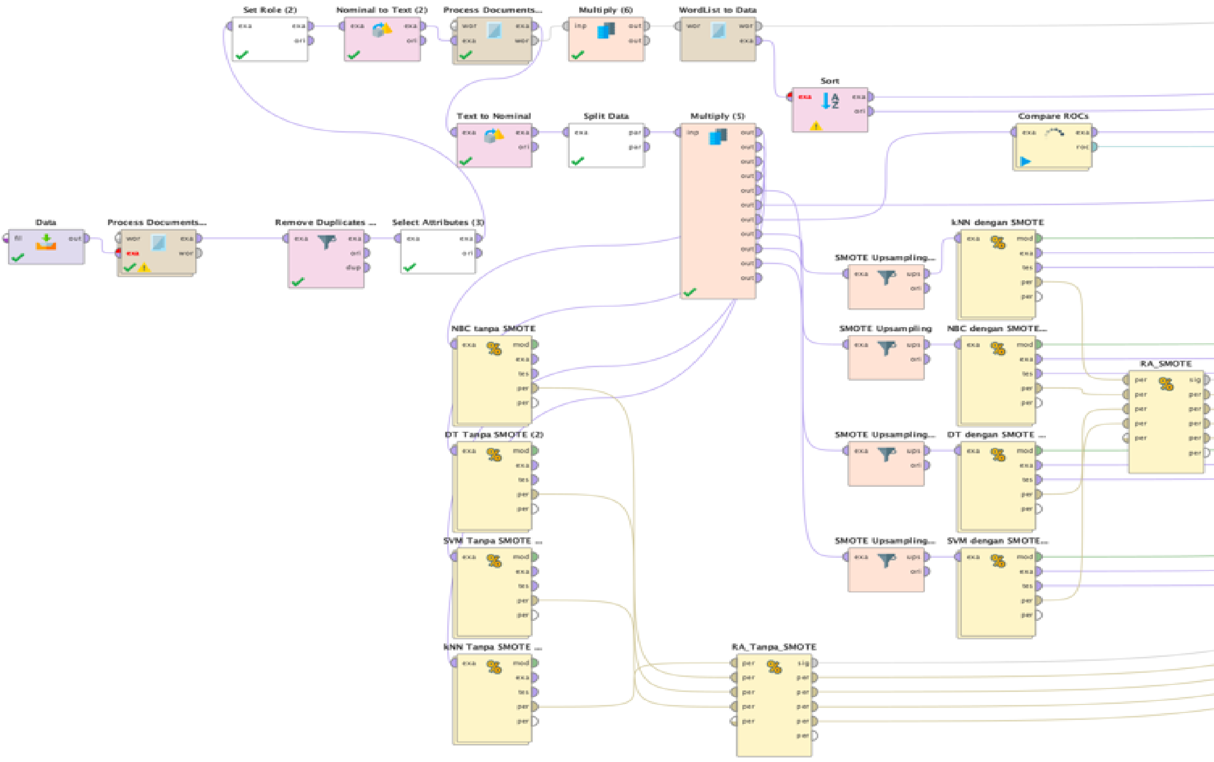

Figure 8. Implementation of K-NN, NBC, DT, and SVM as Sentiment Classification Model

Figure 8 shows the implementation of k-NN, DT, NBC, and SVM as sentiment classification models in Rapidminer. The configuration for splitting the data involves using 30% as training data and 70% as testing data. This approach aims to evaluate the performance of algorithms or machines in learning from the 30% training data and apply this knowledge to the remaining 70% testing data. Using this division, the study ensures that the model is trained on a representative subset and tested on a more significant portion to validate its accuracy and generalizability. This methodology provides a robust framework for assessing the effectiveness of machine learning algorithms in real-world applications, ensuring reliable and meaningful results.

The SMOTE operator is utilized in the algorithm performance testing process to address the issue of data imbalance due to disproportionate class distributions (positive or negative). This operator effectively synthesizes new instances of the minority class, thereby balancing the dataset and enhancing the reliability of the analysis. By mitigating the skewed distribution, SMOTE ensures that the algorithms are trained on a more representative dataset, improving the results' accuracy and generalizability. Consequently, incorporating SMOTE in the testing process is crucial for obtaining robust and valid performance metrics from the evaluated algorithms.

Thus, in the modeling stage, the performance of Communalytic and RapidMiner are compared to evaluate the efficacy of sentiment analysis models. This comparison involves analyzing each tool's accuracy, precision, and robustness in processing and interpreting sentiment data. By benchmarking these platforms, the study identifies which tool offers superior performance in sentiment analysis. Consequently, the insights gained from this comparison will inform best practices for selecting and implementing sentiment analysis tools, enhancing the overall reliability and validity of the research findings.

2.2.4 Evaluation

The Evaluation stage of the CRISP-DM framework is crucial for assessing the model's performance and ensuring its validity. This phase involves rigorous testing of the model against predefined criteria to determine its accuracy, reliability, and effectiveness in addressing the business objectives. By analyzing the results and comparing them with the expected outcomes, potential issues and areas for improvement are identified. This critical evaluation ensures the model meets the necessary standards and is confidently deployed in real-world applications. Ultimately, the Evaluation stage solidifies the model's credibility, ensuring it delivers actionable and reliable insights.

In this research context, the best model's evaluation is determined through metrics such as the confusion matrix, accuracy, precision, recall, F-measure, and Area Under Curve (AUC). These metrics comprehensively assess the model's performance by measuring its ability to classify data and handle imbalances correctly. The confusion matrix offers detailed insights into the types of classification errors, while accuracy, precision, and recall quantify the model's overall effectiveness. The F-measure balances precision and recall, and the AUC measures the model's capability to distinguish between classes. Consequently, these evaluation criteria are essential for identifying this study's most robust and reliable model for sentiment analysis.

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The evaluation results of the sentiment analysis and toxicity score calculation for video content in this study reveal critical insights into viewer engagement and sentiment trends. The sentiment analysis using advanced algorithms highlights the prevalence of positive, negative, and neutral sentiments, offering a nuanced understanding of audience reactions. The toxicity score calculation, leveraging the Perspective API, quantifies the levels of toxic language, providing a measure of the discourse quality. These findings underscore the importance of monitoring and managing online interactions to foster a healthier digital environment. Consequently, the combined analysis of sentiment and toxicity scores delivers valuable insights for content creators and platform managers aiming to enhance user experience and engagement.

2.2.5 Deployment

The deployment stage of the CRISP-DM framework is essential for implementing the developed models in practical applications. This phase involves integrating the model into the existing system or workflow, ensuring it operates seamlessly and delivers the anticipated benefits. Key activities include setting up the model's operational environment, establishing monitoring protocols, and providing user training for effective utilization. By addressing these aspects, the deployment ensures that the model's predictive insights are readily accessible and actionable. Consequently, a successful deployment maximizes the model's impact, driving improved decision-making and operational efficiency within the organization.

The deployment of this research involves integrating the developed sentiment analysis and toxicity scoring models into practical applications for content evaluation. This process includes embedding the models into the relevant digital platforms to analyze user comments and generate real-time insights automatically. By setting up a robust monitoring system, the deployment ensures continuous assessment and refinement of the models to maintain accuracy and relevance. This integration facilitates immediate feedback for content creators and platform managers, enhancing the ability to manage and respond to audience interactions effectively. Ultimately, the deployment phase ensures that the research findings are translated into actionable strategies, optimizing user engagement and content quality.

3. RESULT AND DISCUSSION

The discussion in this research is divided into three sections: toxicity analysis results, model performance evaluation, and video content's impact on tourism branding. The toxicity analysis results provide insights into the prevalence of harmful language and its implications for online discourse. The evaluation of model performance examines the effectiveness of various algorithms in accurately classifying sentiment and toxicity, highlighting the most reliable methods. Lastly, the impact on tourism branding assesses how the video content influences public perception and engagement with the destination. These sections collectively offer a comprehensive understanding of digital content's effects and analytical models' effectiveness.

3.1 Toxicity Score and Analysis (Communalytic)

In the first stage, the data processing results using Communalytic for calculating toxicity scores, based on the performance of two machine learning APIs—Detoxify and Perspective API—reveal various metrics, including Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat. These metrics provide a detailed assessment of the harmful language present in the content, enabling a comprehensive understanding of its impact. Using both APIs ensures a robust analysis by cross-verifying the results, enhancing the reliability of the findings. Consequently, this stage establishes a critical foundation for evaluating the extent of toxic behavior in digital content, informing subsequent analysis and discussions.

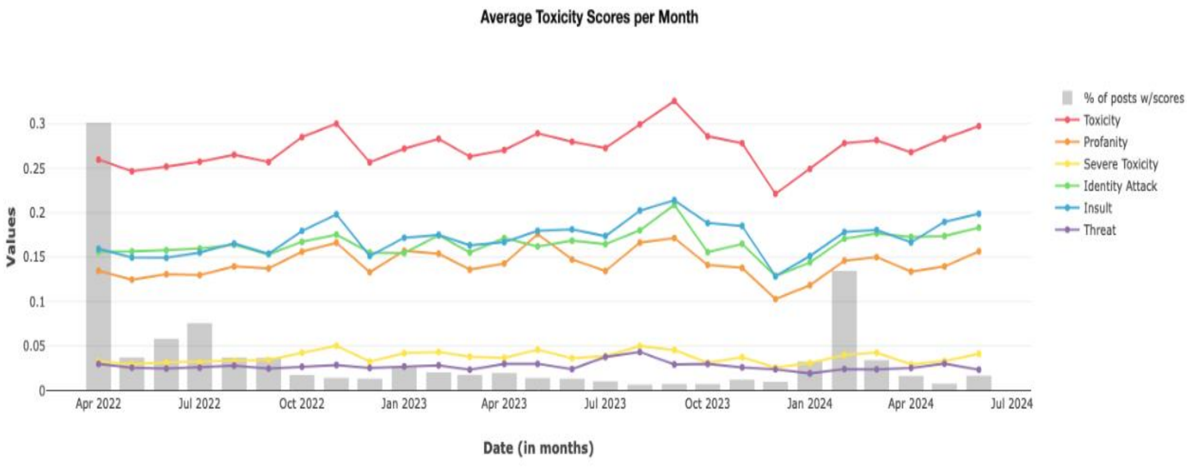

Figure 9. Toxicity Score (Communalytic)

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Figure 9 shows the toxicity score based on the score per month. Based on the calculation of the average toxicity score per month, the following values were observed: Toxicity (0.26614 to 0.98808), Severe Toxicity (0.03546 to 0.64743), Identity Attack (0.16167 to 0.83300), Insult (0.16544 to 0.88346), Profanity (0.13883 to 0.96028), and Threat (0.02704 to 0.67387). These scores indicate a significant presence of harmful language, with varying degrees of severity across different categories. The fluctuations in monthly averages reflect the dynamic nature of online interactions and the varying intensity of toxic behavior over time. Consequently, these insights emphasize the need for continuous monitoring and mitigation strategies to effectively manage and reduce toxicity in digital content.

The toxicity scores range from 0.26614 to 0.98808, indicating a broad spectrum of harmful language presence. Severe Toxicity scores, ranging from 0.03546 to 0.64743, suggest fewer instances but higher severity when they occur. Identity Attack scores, between 0.16167 and 0.83300, reflect targeted harmful comments, whereas Insult scores (0.16544 to 0.88346) indicate frequent derogatory language. Profanity scores, ranging from 0.13883 to 0.96028, show high usage of offensive language, and Threat scores (0.02704 to 0.67387) reveal severe but occasional threats. These scores underscore the pervasive nature of toxic behavior online and highlight the need for robust monitoring and intervention strategies to mitigate such issues effectively.

3.2 Sentiment Analysis (Communalytic and Rapidminer)

Based on the classification of 23,292 out of 25,361 posts in Communalytic using the Vader and TextBlob models, the sentiment distribution is as follows: VADER (English) classified 23,143 posts with 9,066 (39.17%) negative, 3,941 (17.03%) neutral, and 10,136 (43.80%) positive sentiments. TextBlob (English) classified the identical 23,143 posts with 6,141 (26.54%) negative, 8,211 (35.48%) neutral, and 8,791 (37.99%) positive sentiments. Additionally, TextBlob (French) classified 77 posts with 3 (3.90%) negative, 62 (80.52%) neutral, and 12 (15.58%) positive sentiments, while TextBlob (German) classified 69 posts with 1 (1.45%) negative, 60 (86.96%) neutral, and 8 (11.59%) positive sentiments. These results indicate a variance in sentiment detection between the models and languages, reflecting the complexity of sentiment analysis across different linguistic contexts. Consequently, these findings highlight the importance of using multiple models to understand sentiment in diverse datasets comprehensively.

The analysis of the performance of the Vader and TextBlob models reveals significant insights into the impact on content evaluation. Vader, which classified 23,143 posts, identified a higher percentage of positive sentiments (43.80%) compared to TextBlob (37.99%) but also a higher percentage of negative sentiments (39.17% versus 26.54%). TextBlob, however, demonstrated a more remarkable ability to classify neutral sentiments, with 35.48% compared to Vader's 17.03%. This discrepancy indicates that while Vader may be more sensitive to polarized sentiments, TextBlob provides a more balanced view, capturing a broader range of emotional nuances. The impact of these differences is critical for content analysis, as the choice of model influences the perceived sentiment of the content, thereby affecting strategic decisions based on these insights. Consequently, employing both models offers a more comprehensive sentiment analysis, ensuring a robust evaluation of the content's emotional impact.

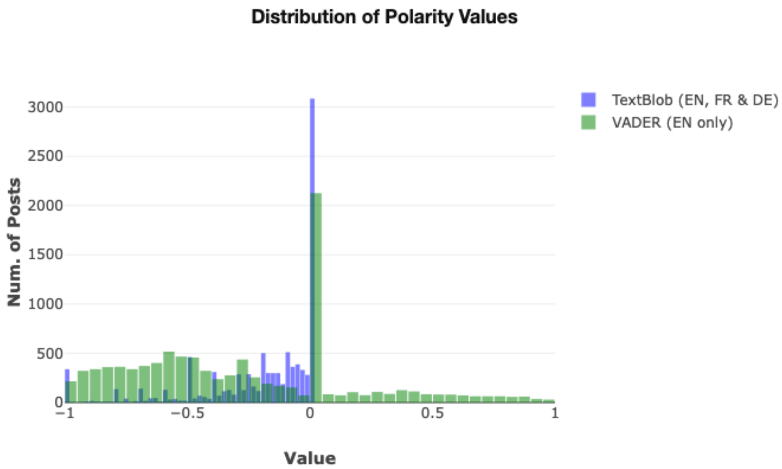

Figure 10. Distribution of Polarity Values

Figure 10 shows the distribution of polarity values. VADER and TextBlob agree on categorizing 13,333 (58.70%) out of 22,714 English language posts, indicating a fair level of agreement (Cohen's kappa statistic = 0.382). Specifically, both libraries concur on the classification of 4,428 (33.21%) posts with negative sentiments (polarity scores <= -0.05), 2,766 (20.75%) posts with neutral sentiments (polarity scores between -0.05 and 0.05), and 6,139 (46.04%) posts with positive sentiments (polarity scores >= 0.05). This level of agreement underscores the models' consistency in sentiment detection yet highlights the nuances in how each model interprets sentiment. Consequently, while the agreement rate is substantial, incorporating multiple sentiment analysis tools provides a more nuanced and comprehensive understanding of the content's emotional tone.

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Further analysis reveals discrepancies in sentiment classification between VADER and TextBlob. Specifically, there were 1,177 posts where VADER assigned positive polarity scores while TextBlob assigned negative scores. Conversely, there were 1,876 posts where VADER assigned negative polarity scores, and TextBlob assigned positive scores. These inconsistencies highlight the differences in sentiment detection algorithms used by the two models, suggesting variability in how they interpret and categorize sentiments. Consequently, such discrepancies underscore the importance of using multiple sentiment analysis tools to achieve a more balanced and comprehensive understanding of content sentiment.

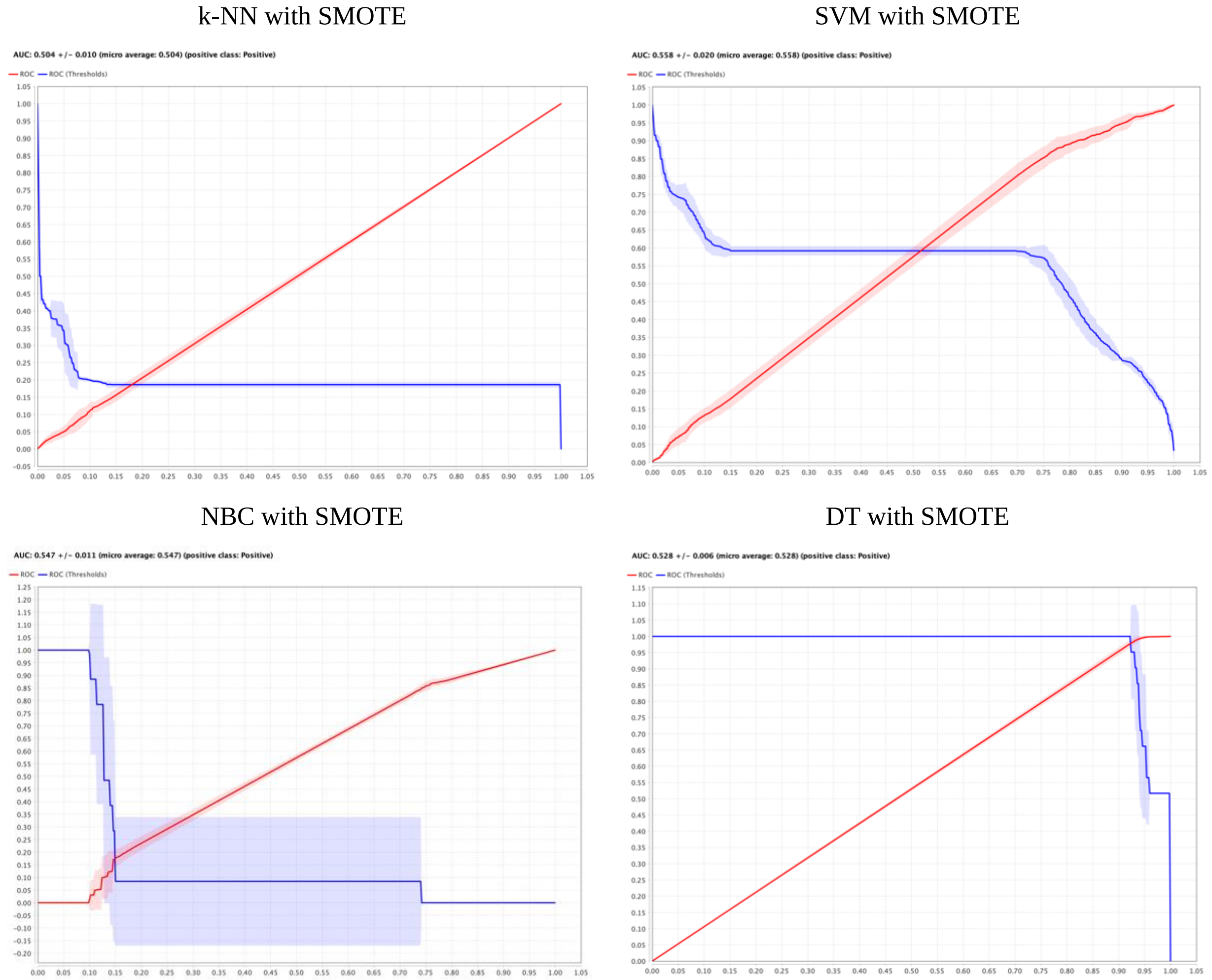

Figure 11. Area Under Curve of k-NN, SVM, NBC, and DT using SMOTE (Rapidminer)

Figure 11 shows the AUC of k-NN, SVM, NBC, and DT using SMOTE. The evaluation results of the SVM with the SMOTE model demonstrate its performance across several metrics. The accuracy is recorded at 54.80% ± 1.65%, indicating a moderate level of precision in classification. The confusion matrix shows 599 true negatives, 335 false negatives, 2,154 false positives, and 2,418 true positives. The AUC values vary significantly, with an optimistic AUC of 0.791 ± 0.023, a micro average AUC of 0.558 ± 0.020, and a pessimistic AUC of 0.326 ± 0.023, reflecting differing levels of model confidence. Precision stands at 52.89% ± 0.98%, while recall is notably higher at 87.83% ± 2.72%, indicating the model's strength in identifying positive instances. The F-measure, balancing precision and recall, is 66.01% ± 1.37%, underscoring the overall effectiveness of the SVM with SMOTE in handling imbalanced datasets. These results suggest that while the model is proficient in recall, there is room for improved precision and overall accuracy to enhance its performance further.

The evaluation results of the k-NN with the SMOTE model highlight its performance across several metrics. The accuracy is recorded at 50.02% ± 0.13%, indicating a low level of precision in classification. The confusion matrix reveals 2,749 true negatives, 2,748 false negatives, four false positives, and five true positives, illustrating significant misclassifications. The AUC values vary considerably, with an optimistic AUC of 0.895 ± 0.019, a micro average AUC of 0.504 ± 0.010, and a pessimistic AUC of 0.112 ± 0.010, indicating inconsistencies in model confidence. Precision is recorded at 55.56%, while recall is notably low at 0.18% ± 0.26%, highlighting the model's struggle to identify positive instances. The F-measure, balancing precision and recall, is a mere 0.36%, underscoring the overall ineffectiveness of the k-NN with SMOTE in handling the given dataset. These results suggest that while the model demonstrates some capability in precision, its overall performance is hindered by poor recall and accuracy, indicating a need for significant improvement.

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The Decision Tree (DT) evaluation results with the SMOTE model indicate its performance across various metrics. The accuracy is recorded at 52.82% ± 0.57%, suggesting moderate precision in classification. The confusion matrix shows 160 true negatives, five false negatives, 2,593 false positives, and 2,748 true positives. The AUC values exhibit significant variability, with an optimistic AUC of 0.998 ± 0.002, a micro average AUC of 0.528 ± 0.006, and a pessimistic AUC of 0.058 ± 0.011, reflecting different levels of model confidence. Precision is recorded at 51.45% ± 0.30%, while recall is exceptionally high at 99.82% ± 0.19%, indicating the model's strength in identifying positive instances. The F-measure, balancing precision and recall, stands at 67.90% ± 0.28%, demonstrating the model's overall effectiveness. These results suggest that while the Decision Tree with SMOTE excels in recall, its moderate accuracy and precision indicate areas for potential improvement to enhance overall performance.

The Naive Bayes Classifier (NBC) evaluation results with the SMOTE model indicate its performance across several metrics. The accuracy is recorded at 51.60% ± 2.13%, reflecting moderate precision in classification. The confusion matrix shows 2,231 true negatives, 2,143 false negatives, 522 false positives, and 610 true positives. The AUC values vary, with an optimistic AUC of 0.778 ± 0.014, a micro average AUC of 0.547 ± 0.011, and a pessimistic AUC of 0.334 ± 0.012, indicating fluctuating levels of model confidence. Precision is recorded at 53.96% ± 5.61%, while recall is significantly lower at 22.17% ± 22.23%, highlighting the model's difficulty in identifying positive instances. The F-measure, balancing precision and recall, stands at 27.87% ± 13.68%, demonstrating the model's overall performance. These results suggest that while the Naive Bayes Classifier with SMOTE shows moderate accuracy, its low recall and F-measure indicate a need for substantial improvements to enhance its effectiveness in sentiment analysis.

The suboptimal accuracy and AUC values of the k-NN, DT, NBC, and SVM algorithms are attributed to several factors. Firstly, the dataset's inherent complexity and imbalanced nature pose significant challenges, leading to difficulty in accurately classifying the data. Additionally, the noise and variability within the dataset impede the algorithms' ability to learn and generalize effectively. Another contributing factor is the potential mismatch between the chosen algorithms and the specific characteristics of the data, suggesting that more sophisticated or tailored models might be necessary. Consequently, these factors collectively contribute to the less-than-ideal performance metrics observed, highlighting the need for further refinement and optimization of the models.

3.3 Discussion

The toxicity analysis results during this research's deployment stage reveal significant insights into user engagement. The toxicity scores, derived from evaluating user comments, indicate varying levels of harmful language and its potential impact on the community. High toxicity levels are correlated with decreased user engagement, as toxic environments often discourage participation and interaction. Conversely, managing and mitigating toxicity fosters a more positive and inclusive atmosphere, enhancing user engagement [34], [34]. These findings underscore the critical role of monitoring and addressing toxicity in digital platforms to maintain a healthy user community and encourage active participation.

The sentiment analysis results on the tourism destination brand within the content reveal critical insights into public perception. The analysis shows a predominance of positive sentiments, reflecting favorable opinions and high user satisfaction levels [35], [36]. However, a notable portion of negative sentiments highlights specific areas of concern that could impact the overall brand image [37]–[39]. These mixed sentiments suggest that while the destination is generally well-received, addressing negative feedback is essential for maintaining and enhancing its reputation [40], [41]. Consequently, leveraging these insights informs targeted strategies to improve user experiences and bolster the destination's brand appeal.

Several recommendations were made for content creators based on the toxicity and sentiment analysis results. Firstly, actively monitoring and addressing toxic comments enhance the user experience and foster a more positive community environment. Additionally, constructively leveraging positive feedback and addressing negative sentiments improve content quality and audience engagement [42], [42]. Implementing strategies such as content moderation and engaging with viewers' concerns mitigate the impact of toxic behavior. Ultimately, these practices enhance user satisfaction and strengthen the content creator's brand reputation and audience loyalty.

The limitations of this research are noteworthy and impact the generalizability of the findings. One primary limitation is the reliance on specific sentiment analysis models, which may not capture the full complexity of user emotions and could introduce bias. Additionally, the dataset's inherent imbalance and noise could affect the accuracy and reliability of the toxicity scores and sentiment classifications. Furthermore, the study's focus on a single platform may limit the applicability of the results to other digital environments. These limitations suggest the need for broader studies incorporating diverse datasets and advanced analytical methods to enhance the robustness and applicability of the research outcomes.

Based on the findings of this research, several recommendations are proposed to enhance content creation and user engagement. Firstly, content creators should implement robust moderation strategies to manage and mitigate toxicity, fostering a more positive community environment. Additionally, leveraging sentiment analysis insights to tailor content that resonates with audience preferences improves engagement and satisfaction. Diversifying the analytical tools and datasets used in future research is also advisable to ensure more comprehensive and accurate sentiment assessments. Ultimately, these recommendations aim to optimize content quality and audience interaction, strengthening digital content's overall impact and reach.

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4. CONCLUSION

In conclusion, this research, structured around the CRISP-DM framework, comprehensively analyzes sentiment and toxicity in digital content, focusing on tourism-related videos. Throughout the six stages of CRISP-DM—Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment—the study utilized advanced machine learning models, including VADER and TextBlob, to evaluate sentiment and APIs such as Detoxify and Perspective to assess toxicity levels. Specifically, 25,361 posts were analyzed, with 23,292 posts processed for sentiment analysis and 24,171 for toxicity assessment. Various algorithms, including k-NN, DT, NBC, and SVM, were applied with SMOTE to address data imbalance, resulting in performance metrics such as SVM's accuracy of 54.80% and F-measure of 66.01%. At the same time, k-NN and DT exhibited lower accuracy and recall rates. The deployment phase integrated these models into practical applications for real-time analysis of user comments, generating actionable insights. The findings highlight the impact of positive and negative sentiments on brand perception and audience interaction, emphasizing the importance of managing toxic behavior to foster a healthier online environment. Despite limitations like dataset imbalance and model reliance, the study provides valuable recommendations for content creators, advocating for effective moderation strategies and leveraging sentiment insights to enhance user engagement. Future research should incorporate more diverse datasets and advanced analytical tools to improve the robustness and generalizability of the findings. Through the CRISP-DM methodology, this research contributes to a deeper understanding of digital content dynamics. It offers actionable insights for optimizing content creation and user interaction, thus enhancing the strategic management of digital content and its impact on audience engagement.

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REFERENCES

[1] H. Jang, B. Barrett, and S. C. McGregor, "Social media policy in two dimensions: understanding the role of anti-establishment beliefs and political ideology in Americans' attribution of responsibility regarding online content," *Inf. Commun. Soc.*, 2023, doi: 10.1080/1369118X.2023.2234970.
[2] J. Sihvonen and L. L. M. Turunen, "Multisensory experiences at travel fairs: What evokes feelings of pleasure, arousal and dominance among visitors?," *J. Conv. Event Tour.*, vol. 23, no. 1, pp. 63–85, 2022, doi: 10.1080/15470148.2021.1949417.
[3] M. Li, M. Cheng, V. Quintal, and I. Cheah, "From live streamer to viewer: exploring travel live streamer persuasive linguistic styles and their impacts on travel intentions," *J. Travel Tour. Mark.*, vol. 40, no. 8, pp. 764–777, 2023, doi: 10.1080/10548408.2023.2294071.
[4] A. Tresa Sebastian *et al.*, "Exploring the opinions of the YouTube visitors towards advertisements and its influence on purchase intention among viewers," *Cogent Bus. Manag.*, vol. 8, no. 1, 2021, doi: 10.1080/23311975.2021.1876545.
[5] T. Godskesen, S. Frygner Holm, A. T. Höglund, and S. Eriksson, "YouTube as a source of information on clinical trials for paediatric cancer," *Inf. Commun. Soc.*, vol. 26, no. 4, pp. 716–729, 2023, doi: 10.1080/1369118X.2021.1974515.
[6] C. Arkenback, "YouTube as a site for vocational learning: instructional video types for interactive service work in retail," *J. Vocat. Educ. Train.*, vol. 00, no. 00, pp. 1–27, 2023, doi: 10.1080/13636820.2023.2180423.
[7] V. Valta, "Making a Narrative of Repetition: Diachronicity and the Second-Person Address in YouTube's Routine Videos," *Life Writ.*, pp. 1–20, 2024, doi: 10.1080/14484528.2024.2324997.
[8] E. Burrai, D. M. Buda, and E. Stevenson, "Tourism and refugee-crisis intersections: co-creating tour guide experiences in Leeds, England," *J. Sustain. Tour.*, vol. 31, no. 12, pp. 2680–2697, 2023, doi: 10.1080/09669582.2022.2072851.
[9] J. Struwig and E. A. du Preez, "Evolving domestic tourism destination preferences post-apartheid," *J. Leis. Res.*, vol. 0, no. 0, pp. 1–30, 2024, doi: 10.1080/00222216.2024.2336073.
[10] E. Burrai, D. Buda, and E. Stevenson, "Tourism and refugee-crisis intersections : co- creating tour guide experiences in Leeds , England," *J. Sustain. Tour.*, vol. 31, no. 12, pp. 2680–2697, 2023, doi: 10.1080/09669582.2022.2072851.
[11] J. Struwig and E. Ann, "Evolving domestic tourism destination preferences," *J. Leis. Res.*, vol. 0, no. 0, pp. 1–30, 2024, doi: 10.1080/00222216.2024.2336073.
[12] E. Tverijonaite, A. D. Sæþórsdóttir, R. Ólafsdóttir, and C. M. Hall, "Wilderness: a resource or a sanctuary? Views of tourism service providers," *Scand. J. Hosp. Tour.*, vol. 23, no. 2–3, pp. 195–225, 2023, doi: 10.1080/15022250.2023.2233932.
[13] S. Chen and J. M. Luo, "Assessing barriers to the development of convention tourism in Macau," *Cogent Soc. Sci.*, vol. 7, no. 1, 2021, doi: 10.1080/23311886.2021.1928978.
[14] S. D. Reynolds *et al.*, "Swimming with humans: biotelemetry reveals effects of 'gold standard' regulated tourism on whale sharks," *J. Sustain. Tour.*, vol. 0, no. 0, pp. 1–20, 2024, doi: 10.1080/09669582.2024.2314624.
[15] N. Porto, D. A. Pitetti, and M. Ciaschi, "A worldwide tourism-extended Environmental Kuznets Curve. New approaches in a comparative analysis," *J. Sustain. Tour.*, vol. 31, no. 9, pp. 2100–2118, 2023, doi: 10.1080/09669582.2021.2023165.
[16] L. J. Salangsang, M. J. Liwanag, and P. A. Notorio, "A content analysis of Asian countries' tourism video advertisements: a luxury travel perspective," *Consum. Behav. Tour. Hosp.*, vol. 17, no. 1, pp. 76–88, Jan. 2022, doi: 10.1108/CBTH-05-2021-0141.
[17] N. Basaraba, "The rise of paranormal investigations as virtual dark tourism on YouTube," *J. Herit. Tour.*, vol. 19, no. 2, pp. 287–309, 2024, doi: 10.1080/1743873X.2023.2268746.

Building of Informatics, Technology and Science (BITS)
Volume 6, No 1, June 2024 Page: 365-377
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ISSN 2685-3310 (media online)
DOI 10.47065/bits.v6i1.5397

[18] P. S. Motahar, R. Tavakoli, and P. Mura, "Social media influencers' visual framing of Iran on YouTube," *Tour. Recreat. Res.*, vol. 0, no. 0, pp. 1–13, 2021, doi: 10.1080/02508281.2021.2014252.
[19] P. Kumar, J. M. Mishra, and Y. V. Rao, "Analysing tourism destination promotion through Facebook by Destination Marketing Organizations of India," *Curr. Issues Tour.*, vol. 25, no. 9, pp. 1416–1431, 2022, doi: 10.1080/13683500.2021.1921713.
[20] H. Jodén and J. Strandell, "Building viewer engagement through interaction rituals on Twitch.tv," *Inf. Commun. Soc.*, vol. 25, no. 13, pp. 1969–1986, 2022, doi: 10.1080/1369118X.2021.1913211.
[21] C. P. Chen, "Hardcore viewer engagement and social exchange with streamers and their digital live streaming communities," *Qual. Mark. Res.*, vol. 26, no. 1, pp. 37–57, Jan. 2023, doi: 10.1108/QMR-06-2021-0074.
[22] W. J. Ladeira, M. Dalmoro, F. de O. Santini, and W. C. Jardim, "Visual cognition of fake news: the effects of consumer brand engagement," *J. Mark. Commun.*, vol. 28, no. 6, pp. 681–701, 2021, doi: 10.1080/13527266.2021.1934083.
[23] Y. Christian and K. O. Y. R. Qi, "Penerapan K-Means pada Segmentasi Pasar untuk Riset Pemasaran pada Startup Early Stage dengan Menggunakan CRISP-DM," *JURIKOM (Jurnal Ris. Komputer)*, vol. 9, no. 4, pp. 966–973, 2022, doi: 10.30865/jurikom.v9i4.4486.
[24] F. Martinez-Plumed *et al.*, "CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories," *IEEE Trans. Knowl. Data Eng.*, vol. 33, no. 8, pp. 3048–3061, 2021, doi: 10.1109/TKDE.2019.2962680.
[25] J. Bokrantz, M. Subramaniyan, and A. Skoogh, "Realising the promises of artificial intelligence in manufacturing by enhancing CRISP-DM," *Prod. Plan. Control*, vol. 0, no. 0, pp. 1–21, 2023, doi: 10.1080/09537287.2023.2234882.
[26] Y. A. Singgalen, "Toxicity Analysis and Sentiment Classification of Wonderland Indonesia by Alffy Rev using Support Vector Machine," *J. Sist. Komput. dan Inform.*, vol. 5, no. 3, pp. 538–548, 2024, doi: 10.30865/json.v5i3.7563.
[27] Y. A. Singgalen, "Digital marketing of smartphone manufacturing product : toxicity , social network , and sentiment classification," *Int. J. Soc. Sci. Econ. Art*, vol. 14, no. 1, pp. 73–86, 2024.
[28] Y. A. Singgalen, "Toxicity , topic , and sentiment analysis on the operation of coal-fired power plants content reviews," *J. Tek. Inform. C.I.T Medicom*, vol. 16, no. 1, pp. 45–57, 2024.
[29] T. Huu Do, M. Berneman, J. Patro, G. Bekoulis, and N. Deligiannis, "Context-Aware Deep Markov Random Fields for Fake News Detection," *IEEE Access*, vol. 9, pp. 130042–130054, 2021, doi: 10.1109/ACCESS.2021.3113877.
[30] S. W. Lin, K. F. Wang, and Y. H. Chiu, "Effects of tourists' psychological perceptions and travel choice behaviors on the nonmarket value of urban ecotourism during the COVID-19 pandemic- case study of the Maokong region in Taiwan," *Cogent Soc. Sci.*, vol. 8, no. 1, 2022, doi: 10.1080/23311886.2022.2095109.
[31] D. Joo, H. Cho, K. M. Woosnam, and C. Suess, "Re-theorizing social emotions in tourism: applying the theory of interaction ritual in tourism research," *J. Sustain. Tour.*, vol. 31, no. 2, pp. 367–382, 2023, doi: 10.1080/09669582.2020.1849237.
[32] J. Sixto-García, A. I. Rodríguez-Vázquez, and X. López-García, "News Sharing Using Self-destructive Content in Digital Native Media from an International Perspective," *Journal. Pract.*, vol. 17, no. 7, pp. 1341–1356, 2023, doi: 10.1080/17512786.2021.2000883.
[33] J. Filipovic and M. Arslanagic-Kalajdzic, "Mirroring digital content marketing framework: capturing providers' perspectives through stimuli assessment and behavioural engagement response," *Eur. J. Mark.*, vol. 57, no. 9, pp. 2173–2198, Jan. 2023, doi: 10.1108/EJM-03-2021-0158.
[34] M. Boukes, X. Chu, M. F. A. Noon, R. Liu, T. Araujo, and A. C. Kroon, "Comparing user-content interactivity and audience diversity across news and satire: differences in online engagement between satire, regular news and partisan news," *J. Inf. Technol. Polit.*, vol. 19, no. 1, pp. 98–117, 2022, doi: 10.1080/19331681.2021.1927928.
[35] P. Stamolampros and D. Dousios, "Employee satisfaction during the pandemic in the tourism and hospitality industries," *Curr. Issues Tour.*, pp. 1–15, 2023, doi: 10.1080/13683500.2023.2268798.
[36] M. Cassar, J. Konietzny, and A. Caruana, "Customer encounter satisfaction and narrative force: an investigation of user-generated content on TripAdvisor," *Scand. J. Hosp. Tour.*, vol. 23, no. 1, pp. 51–72, 2023, doi: 10.1080/15022250.2023.2194272.
[37] I. P. G. Sukaatmadja, N. N. K. Yasa, and P. L. D. Rahmayanti, "Bali brand love: A perspective from domestic tourists," *Cogent Bus. Manag.*, vol. 10, no. 3, 2023, doi: 10.1080/23311975.2023.2260119.
[38] D. Amani and E. Chao, "How does destination governance build local residents' behavioural support towards destination branding: An empirical study of the tourism sector in Tanzania," *Cogent Soc. Sci.*, vol. 9, no. 1, 2023, doi: 10.1080/23311886.2023.2192441.
[39] H. Shi, Y. Liu, T. Kumail, and L. Pan, "Tourism destination brand equity, brand authenticity and revisit intention: the mediating role of tourist satisfaction and the moderating role of destination familiarity," *Tour. Rev.*, vol. 77, no. 3, pp. 751–779, Jan. 2022, doi: 10.1108/TR-08-2021-0371.
[40] S. W. Lee and K. Xue, "A model of destination loyalty: integrating destination image and sustainable tourism," *Asia Pacific J. Tour. Res.*, vol. 25, no. 4, pp. 393–408, 2020, doi: 10.1080/10941665.2020.1713185.
[41] S. Tanaka, C. Kim, H. Takahashi, and A. Nishihara, "Impact of brand authenticity on word-of-mouth for tourism souvenirs," *Cogent Bus. Manag.*, vol. 11, no. 1, 2023, doi: 10.1080/23311975.2023.2290222.
[42] W. Tafesse, "YouTube marketing: how marketers' video optimization practices influence video views," *Internet Res.*, vol. 30, no. 6, pp. 1689–1707, Jan. 2020, doi: 10.1108/INTR-10-2019-0406.

