



# Digital marketing of smartphone manufacturing product: toxicity, social network, and sentiment classification

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## Article Info

### Article history:

Received: Mar 08, 2024

Revised: Mar 30, 2024

Accepted: Apr 08, 2024

### Keywords:

Digital Marketing;  
Sentiment Classification;  
Social Network;  
Support Vector Machine;  
Toxicity Analysis.

## ABSTRACT

This research explores digital interactions, analyzing toxicity, sentiment, and network dynamics using the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology. Understanding and managing these elements are crucial for effective digital strategies with the rise of user-generated content. Leveraging machine learning, including Support Vector Machines (SVM) and Synthetic Minority Over-sampling Technique (SMOTE), toxicity analysis and sentiment classification are conducted. Data preprocessing involves text cleaning and feature engineering, aligning with the CRISP-DM data preparation phase. Toxicity levels are measured using various toxicity metrics, including Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat. Sentiment analysis employs SVM to classify sentiment polarity, while SMOTE addresses class imbalance as part of the CRISP-DM modeling phase. Social Network Analysis (SNA) techniques are also applied to study network structures following the CRISP-DM modeling phase. Network data are processed to compute key SNA metrics such as Diameter, Density, Reciprocity, Centralization, and Modularity. Findings reveal a toxicity level of 0.06194 and severe toxicity at 0.00730. Identity Attack stands at 0.0107, while insults and profanity are at 0.03803 and 0.04905, respectively. The threat is observed at 0.01359. The sentiment analysis indicates an accuracy of 97.94%, with a precision and recall of 98.07% and 99.86%, respectively, for the positive class. The f-measure for the positive class is 98.96%. The SNA metrics show a diameter of 4, a density of 0.000266, and a reciprocity of 0.000000. Centralization is calculated at 0.001468, while modularity stands at 0.999400.

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## 1. INTRODUCTION

Digital marketing is pivotal in enhancing business profitability through its multifaceted impact on contemporary commerce. Integrating digital marketing strategies empowers businesses to reach a broader audience, expanding their market presence and potential customer base (Comai, 2023). By leveraging various online channels such as social media, search engine optimization, and email

campaigns, companies can efficiently connect with consumers in real time, fostering engagement and brand loyalty (Dewantara et al., 2023; Stegmann et al., 2023; Zahay, 2021). Furthermore, the data analytics capabilities inherent in digital marketing platforms enable businesses to glean valuable insights into consumer behavior, facilitating targeted and personalized marketing campaigns (Cavdar Aksoy et al., 2021; Phuong Dung et al., 2023; Smith, 2022; Vieira et al., 2022). This ability to tailor approaches to specific demographics enhances the overall effectiveness of promotional efforts, ultimately driving sales and revenue (Martínek et al., 2023). In conclusion, the strategic implementation of digital marketing amplifies a business's online visibility and optimizes its outreach, fostering a symbiotic relationship between consumer engagement and increased profitability.

Video content showcasing the manufacturing process significantly enhances consumer trust and confidence in digital marketing campaigns for smartphone products. Through immersive visual narratives, potential buyers gain firsthand insights into the intricate processes of crafting these devices, thereby fostering a deeper understanding and appreciation of the product's quality and craftsmanship (Santoso et al., 2020). Moreover, witnessing the manufacturing journey instills a sense of transparency and authenticity, crucial elements in today's consumer landscape driven by authenticity and brand credibility (Das et al., 2023). Consequently, leveraging video content to showcase the smartphone production process informs and persuades consumers, ultimately increasing brand affinity and purchase intent (Xie & Lou, 2024; Zollo et al., 2022). In essence, employing such multimedia strategies effectively bridges the gap between product offerings and consumer trust, bolstering the success of digital marketing initiatives in promoting smartphone products.

Consumer confidence in purchasing products is often sparked by their understanding of the product manufacturing process. When consumers have insight into how a product is made, they develop a deeper appreciation for its quality and authenticity (Utami et al., 2021; Wilson-Nash & Tinson, 2022). Understanding the intricacies of production imbues consumers with a sense of trust towards the brand, as it signifies transparency and commitment to delivering a superior product (Hongcharu, 2024). This comprehension of the manufacturing process informs consumers and instills a sense of reliability and credibility in their purchase decisions (Wandoko & Panggati, 2022). In essence, the clarity provided by understanding the production process catalyzes consumer confidence, significantly influencing their purchasing behavior and fostering long-term brand loyalty.

This research analyzes consumer sentiments toward digital marketing content encompassing the product assembly process. The investigation aims to dissect the emotions and perceptions expressed by consumers when exposed to marketing materials, highlighting the intricate stages of product assembly (Filep et al., 2023; Rana et al., 2024). By delving into these sentiments, valuable insights can be gleaned regarding the effectiveness of such content in influencing consumer attitudes and preferences (Ponsree et al., 2023; Stewart & Perren, 2023). The study seeks to discern whether a transparent portrayal of the assembly process positively impacts consumer trust and brand credibility (Gupta et al., 2024; Nayal & Pandey, 2022). Through rigorous sentiment analysis, this research aspires to contribute to refining digital marketing strategies, facilitating a more targeted and resonant approach that aligns with consumer expectations (Yazdanparast & Tran, 2021). In conclusion, analyzing consumer sentiments in response to content featuring product assembly processes can shape future marketing endeavors, fostering a deeper understanding of the symbiotic relationship between consumer perception and effective digital marketing strategies.

This research employs a case study approach focusing on video content from the GadgetIn channel, explicitly examining the video with the code U76imVp-OgQ, which showcases the smartphone assembly process before market release. By scrutinizing this content, the study aims to extract insights into consumer perceptions and reactions toward the transparent portrayal of product assembly. Through meticulous analysis of viewer engagement, comments, and sentiment indicators, the research seeks to elucidate the effectiveness of such content in bolstering consumer trust and confidence in the brand (Herzog et al., 2022). By leveraging this specific case study, the research provides valuable empirical evidence regarding the impact of showcasing product assembly processes

on consumer behavior and brand perception (Chatterjee et al., 2023). In conclusion, this case study offers a systematic approach to unraveling the complexities surrounding consumer sentiments in response to digital marketing content featuring product assembly, thus contributing to a deeper understanding of effective marketing strategies in the digital age.

The urgency of this research lies in its potential to address critical gaps in understanding consumer behavior and preferences within digital marketing. With the rapid evolution of technology and the increasing prevalence of online commerce, businesses must continually adapt their marketing strategies to remain competitive (Hall et al., 2021). By investigating consumer sentiments toward digital marketing content featuring product assembly processes, this research aims to provide actionable insights for marketers striving to enhance brand credibility and consumer trust (Svahn & Kristensson, 2022). Moreover, as consumer expectations for transparency and authenticity continue to rise, there is a pressing need to ascertain the effectiveness of such marketing approaches in fostering long-term brand loyalty (Antenucci & Tomasello, 2023). In conclusion, the timeliness of this research is underscored by its relevance to contemporary marketing challenges and its potential to inform strategic decision-making in an increasingly digitalized marketplace.

This research's practical and theoretical implications are rooted in utilizing the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology. CRISP-DM provides a systematic framework for conducting data-driven research, encompassing key stages such as business understanding, data preparation, modeling, evaluation, and deployment. By employing CRISP-DM, this research ensures methodological rigor and transparency, facilitating the reproducibility and validity of findings. Moreover, the theoretical significance lies in applying a well-established industry standard, enhancing the credibility and generalizability of research outcomes within the broader context of data-driven decision-making. In conclusion, adopting the CRISP-DM methodology ensures the practicality and reliability of this research and contributes to advancing theoretical understanding and methodologies in data mining and analytics.

In similar research, numerous studies have delved into consumer perceptions and behaviors in response to digital marketing content, particularly those revealing product assembly processes. These investigations have collectively contributed to a foundational understanding of the impact of transparency on consumer trust and brand loyalty (Ahmed et al., 2023). However, a notable gap in exploring diverse industries and platforms warrants a nuanced examination to discern industry-specific nuances and audience preferences. Therefore, cross-industry comparisons and platform-specific analyses are recommended for future research endeavors to enrich the existing knowledge base and refine digital marketing strategies accordingly. By embracing a comparative approach and exploring different digital channels, researchers can offer more comprehensive insights, aiding businesses in tailoring their strategies to diverse consumer expectations and preferences. In conclusion, while existing research provides a solid foundation, there is a clear opportunity for further exploration and refinement in understanding the intricate dynamics of consumer responses to transparent marketing content in diverse contexts.

## 2. RESEARCH METHOD

### Gap Analysis

The gap analysis of the digital marketing landscape for smartphone products employs Vosviewer, a robust analytical tool renowned for its effectiveness in visualizing and mapping scientific literature. Vosviewer enables a comprehensive examination of existing research and industry publications, facilitating the identification of underexplored areas and gaps in the current discourse surrounding smartphone marketing. This methodological approach empowers researchers and practitioners to pinpoint specific dimensions of digital marketing that require further investigation, thus contributing to a more targeted and strategic research agenda. By leveraging the analytical capabilities of Vosviewer, this research methodology serves as a valuable instrument in elucidating nuanced gaps in the understanding of digital marketing dynamics for smartphone products, offering a



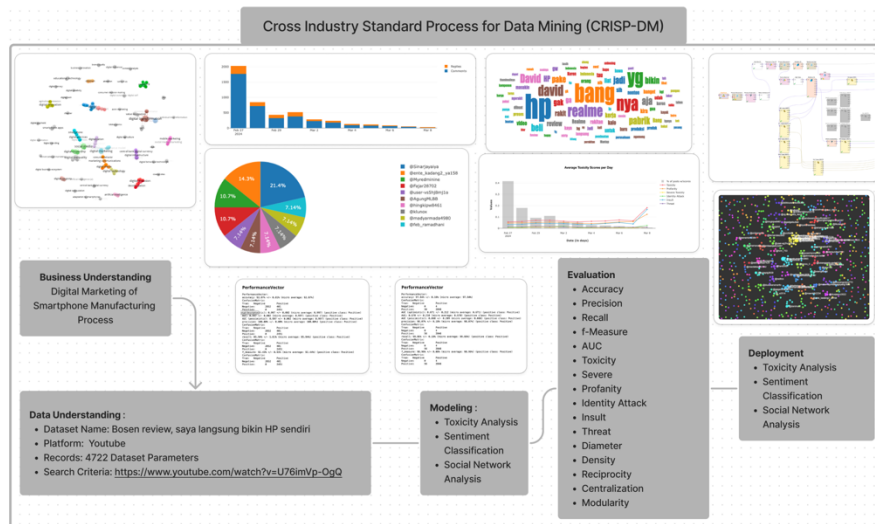


Figure 2. Cross Industry Standard Process for Data Mining (CRISP-DM)

Figure 1 shows the implementation of the CRISP-DM. The framework is contextually limited to analyzing video content from the Gadgetin channel, explicitly focusing on the video with the code U76imVp-OgQ, which has amassed 3.1 million viewers and garnered 4772 comments. While this application of CRISP-DM provides valuable insights into viewer engagement and sentiment towards the featured smartphone product assembly process, its scope is confined to the data available within this specific context. Despite its limitations, this approach allows for a systematic examination of viewer interactions and perceptions, facilitating a nuanced understanding of the effectiveness of digital marketing strategies within the context of the Gadgetin channel. In conclusion, while implementing CRISP-DM is constrained by contextual factors, its application offers valuable insights into viewer engagement and sentiment, thereby contributing to the refinement of digital marketing efforts within the specified channel.

**Business Understanding**

In the initial phase of business understanding, the analysis examines data related to post frequency per day. This analytical process is integral for identifying and understanding consumer interest in video content encompassing the smartphone product assembly process. By scrutinizing the frequency of posts, patterns, and trends emerge, revealing the temporal dynamics of consumer engagement with the content. This phase provides a foundation for recognizing peak periods of interest and tailoring digital marketing strategies accordingly, ensuring that the dissemination of product assembly videos aligns with optimal viewer engagement. Consequently, analyzing post frequency per day is a crucial step in the broader CRISP-DM framework, guiding strategic decisions for content delivery and consumer interaction within the dynamic digital marketing landscape for smartphone products.

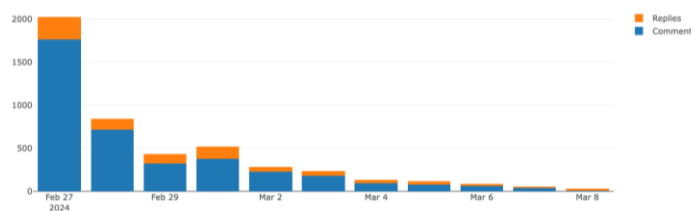


Figure 3. Post Per Day (Communalityc)

Figure 3 shows the post-per-day data using communalistic. The data on post frequency per day, as indicated by the metrics on February 27th (1767 posts, 254 comments), February 28th (718 posts, 124 comments), February 29th (330 posts, 102 comments), March 1st (382 posts, 130 comments), March 2nd (232 posts, 49 comments), and March 3rd (184 posts, 48 comments), provides valuable insights into the temporal dynamics of consumer engagement with the video content featuring the smartphone product assembly process. The variation in post frequency and corresponding comments over this period reflects fluctuating levels of consumer interest. The highest number of posts and comments on February 27th suggests a peak in engagement, while subsequent decreases indicate potential variations in audience interest or external factors influencing viewer interaction. This nuanced understanding of post-frequency dynamics is crucial for formulating targeted and effective digital marketing strategies that align with consumer preferences and optimize engagement. In conclusion, the analysis of post-frequency data serves as a foundational step in decoding consumer behavior and tailoring content dissemination strategies for enhanced effectiveness in the digital marketing landscape.

### Data Understanding

During the data understanding phase, it is imperative to identify the characteristics of the data that will be further analyzed in the modeling process. This initial step lays the groundwork for comprehending the nature and structure of the dataset, including its variables, distributions, and potential patterns. By discerning these key attributes, researchers can effectively preprocess the data and select appropriate modeling techniques that align with the inherent characteristics of the dataset. Additionally, understanding the data's characteristics enables researchers to anticipate potential challenges or limitations in the modeling process, facilitating informed decisions and mitigating risks. Consequently, identifying data characteristics in the data understanding phase is pivotal for ensuring the accuracy, reliability, and relevance of subsequent modeling efforts within the broader context of data-driven research.

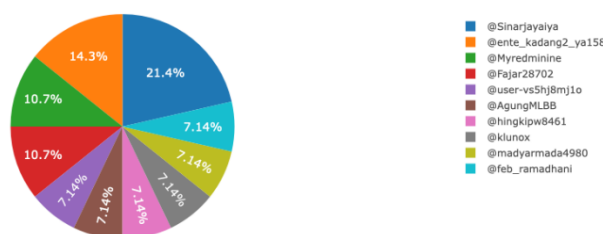


Figure 4. Top Ten Poster (Communalitic)

Figure 4 shows the top ten posters using community. Examining the top ten posters, as indicated by the frequency of their posts, reveals insightful patterns within the dataset. Notably, @Sinarjayaiya emerges as the most prolific contributor with six posts, followed by @ente\_kadang2\_ya158 with four posts and @Myredminine with three. This distribution sheds light on the varying levels of engagement and participation among users, showcasing a notable discrepancy in the frequency of contributions. Multiple users with two or more posts suggest diverse contributors, contributing to a rich and dynamic discussion. This analysis of top contributors is instrumental in understanding the participatory dynamics within the dataset. It may serve as a foundation for targeted engagement strategies or further exploration of user behavior. In conclusion, by recognizing and scrutinizing the top ten posters, researchers gain valuable insights into the diverse landscape of user engagement, fostering a nuanced understanding of the dataset's social dynamics.

### Modeling

In the modeling stage, a crucial initial step involves pre-processing data, focusing on the cleansing process to discern frequently used words. This indispensable process ensures the dataset is refined without noise or irrelevant information, setting the stage for subsequent analysis. Researchers



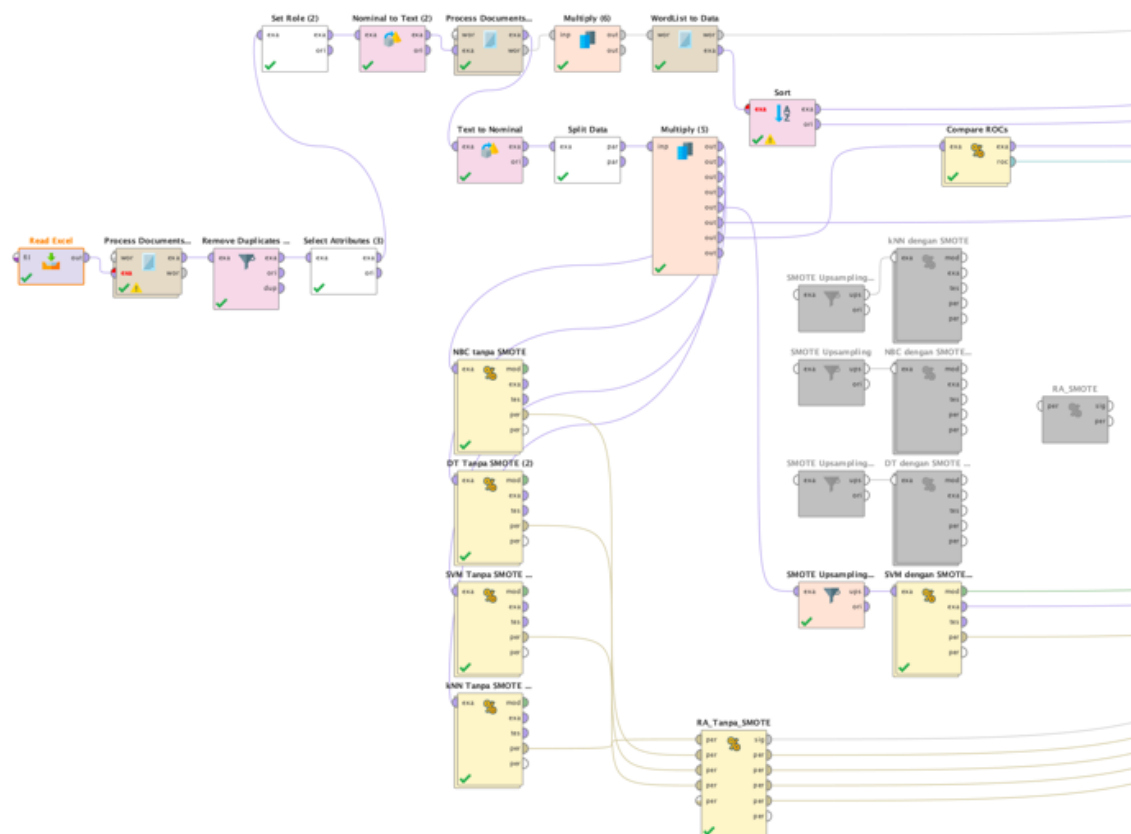


Figure 6. Modeling using Rapidminer

Figure 6 shows the modeling process using SVM and SMOTE in Rapidminer. The performance of SVM and SMOTE in modeling can be assessed through the confusion matrix, which evaluates metrics such as accuracy, precision, recall, F-measure, and Area Under the Curve (AUC). This comprehensive analysis provides a holistic understanding of the model's effectiveness in classification tasks, including correctly identifying true positives, false positives, true negatives, and false negatives. By scrutinizing these metrics, researchers can gauge the model's overall predictive power and reliability, ensuring it meets the desired performance standards. Additionally, evaluating multiple metrics offers a nuanced perspective on the model's strengths and weaknesses, facilitating informed decision-making and iterative refinement of the modeling process. In conclusion, examining performance metrics derived from the confusion matrix is critical in assessing the efficacy and robustness of SVM and SMOTE in data modeling tasks, ultimately contributing to generating accurate and actionable insights.

### Evaluation

In the evaluation stage, a comprehensive assessment is conducted to compare the performance of the SVM algorithm with and without its utilization. This comparative analysis allows researchers to discern the impact of SVM on the overall modeling process and its effectiveness in improving predictive accuracy and classification outcomes. Researchers can ascertain SVM's relative strengths and weaknesses in enhancing model performance by evaluating performance metrics such as accuracy, precision, recall, and F-measure. Additionally, this evaluation facilitates a nuanced understanding of SVM's added value and utility in addressing complex classification tasks, guiding strategic decision-making, and refining modeling techniques. In conclusion, evaluating SVM, both with and without its implementation, is crucial in determining its efficacy and suitability for specific data modeling objectives, ultimately contributing to advancing predictive modeling methodologies.

In evaluating toxicity analysis, the assessment is based on calculating the average values for the entire dataset and identifying the highest values for specific toxicity categories, including Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat. These metrics provide a comprehensive understanding of the prevalence and severity of toxic behavior within the dataset, allowing researchers to discern patterns and trends in harmful discourse. By analyzing the average toxicity scores, researchers can gauge the overall level of toxicity present in the dataset while identifying the highest values for individual toxicity categories, which offers insights into the most prevalent forms of harmful language. This dual approach to evaluation enables researchers to gain nuanced insights into the nature and extent of toxicity within the dataset, informing strategies for mitigating and addressing toxic behavior effectively. In conclusion, the comprehensive evaluation of toxicity analysis metrics is vital in understanding and combating harmful discourse within digital environments, promoting healthier online interactions and communities.

The evaluation of Social Network Analysis (SNA) is conducted based on metrics such as diameter, density, reciprocity, centralization, and modularity, categorized into "who mentions whom" and "who replies to whom" networks. These metrics offer valuable insights into the structural properties and dynamics of social networks, facilitating a comprehensive assessment of interaction patterns and communication flows within the network. By scrutinizing parameters such as diameter and density, researchers can ascertain the extent of connectivity and clustering within the network. At the same time, metrics like reciprocity and centralization provide insights into the symmetry and distribution of influence among network actors. Additionally, the evaluation of modularity offers insights into the presence of cohesive subgroups or communities within the network. In conclusion, the systematic evaluation of SNA metrics provides a holistic understanding of the network's structure and dynamics, enabling researchers to identify critical patterns and phenomena that shape social interactions and relationships within the network.

### **Deployment**

In the deployment stage, the effectiveness of smartphone digital marketing can be vividly illustrated through influencer marketing content showcasing the product assembly process. Leveraging influencers to portray the intricate stages of product assembly enhances brand visibility and fosters consumer trust and engagement. By harnessing the influence and credibility of key opinion leaders, brands can effectively communicate the quality and authenticity of their products, thereby influencing consumer perceptions and purchase decisions. This strategic deployment of influencer marketing content aligns with contemporary consumer preferences for authenticity and transparency, ultimately driving brand affinity and sales. In conclusion, integrating influencer marketing content featuring product assembly processes into digital marketing strategies represents a compelling approach to maximize the impact and effectiveness of smartphone marketing initiatives.

## **3. RESULTS AND DISCUSSIONS**

### **Toxicity Analysis**

Toxicity analysis plays a crucial role in the discernment of textual data containing elements of Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat. This analytical process utilizes advanced algorithms to evaluate the linguistic content for potential harm, enabling the identification and categorization of offensive language and harmful expressions within a given dataset. Researchers can effectively uncover and quantify the extent of negative sentiments, personal attacks, insults, profanity, and threats in textual data by systematically assessing these toxicity dimensions. This information is pivotal for fostering a safer and more inclusive digital environment, as toxicity analysis equips platforms and communities with the tools necessary to detect, monitor, and mitigate harmful content, ultimately enhancing online discourse and creating more respectful and secure online spaces. In conclusion, the strategic application of toxicity analysis emerges as an indispensable instrument in promoting responsible communication and fostering healthier digital interactions.

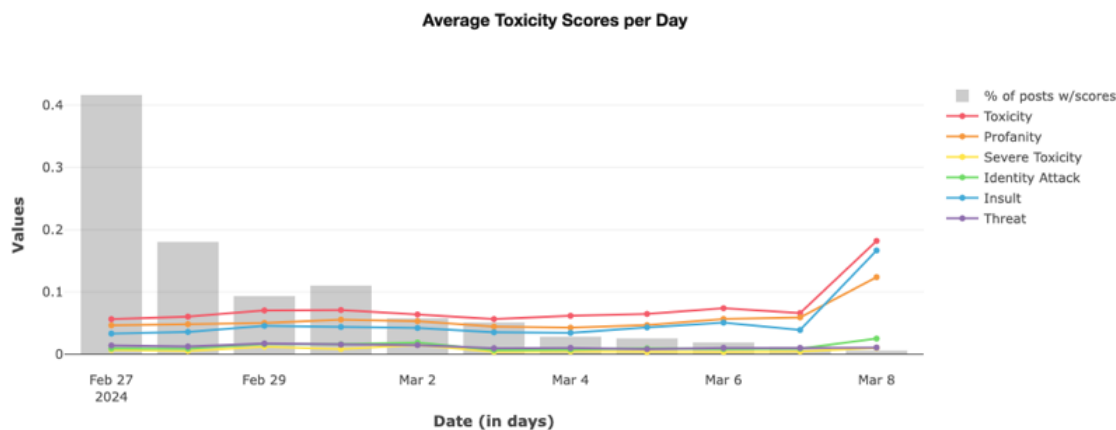


Figure 7. Toxicity Analysis using Communalitic

Based on the results of the toxicity analysis, it is discernible that various dimensions of toxicity exhibit different levels of prevalence within the analyzed dataset. The metrics reveal that Toxicity is observed at 0.06194 with a confidence interval of 0.76499, suggesting a moderate level of toxic language in the dataset. Similarly, Severe Toxicity is identified at 0.00730 with a confidence interval of 0.86893, indicating a relatively low occurrence of severe toxic language. Identity Attack, with a value of 0.0107 and a confidence interval of 0.93566, reflects a minimal presence of attacks on personal identity within the dataset. Furthermore, the metrics for Insult and Profanity stand at 0.03803 and 0.04905, respectively, with confidence intervals of 0.71377 and 0.70384, indicating a moderate prevalence of insulting and profane language. Lastly, Threat is noted at 0.01359 with a confidence interval of 0.93987, revealing a relatively low incidence of threatening language. These findings provide insights into the varying degrees of toxicity within the dataset, highlighting the importance of employing robust toxicity analysis techniques to mitigate harmful language and promote safer digital environments.

### Implementation of SVM and SMOTE

Sentiment classification plays a pivotal role in discerning consumer sentiments towards marketed products. This research employs the SVM and SMOTE, comparing the performance of both models to recommend the most effective one. The SVM algorithm, known for its robustness in handling complex data, is complemented by the SMOTE technique, which addresses class imbalance issues. By evaluating and contrasting the performance of these models, the research aims to identify the most proficient approach for sentiment classification. This methodological scrutiny is essential in advancing the accuracy and reliability of sentiment analysis, thereby aiding businesses in gaining a comprehensive understanding of consumer perceptions and refining their marketing strategies accordingly. In conclusion, the investigation into SVM and SMOTE for sentiment classification is integral to enhancing the efficiency of sentiment analysis in capturing and interpreting consumer sentiments toward marketed products.

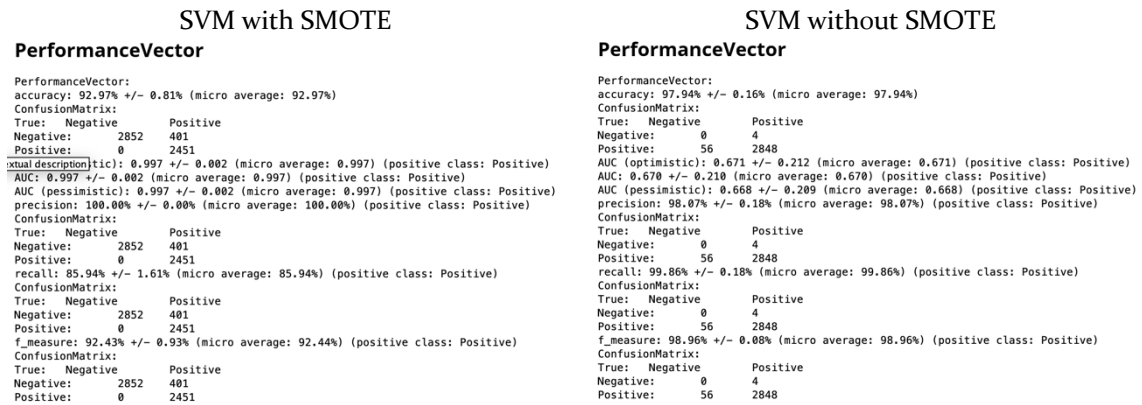


Figure 8. Performance Evaluation of SMV with and without SMOTE

Based on the evaluation results of the SVM performance using SMOTE, it is evident that the model demonstrates high accuracy, with a mean accuracy of 92.97% and a micro average of 92.97%. The confusion matrix illustrates that the model effectively classifies negative and positive instances, with a precision and recall of 100.00% and 85.94%, respectively, for the positive class. Additionally, the model exhibits a robust f-measure of 92.43% for the positive class. These findings highlight the effectiveness of the SVM model in conjunction with SMOTE in accurately classifying sentiments, particularly in distinguishing positive instances. This underscores the significance of employing advanced techniques like SMOTE to address class imbalance issues, thereby enhancing the performance and reliability of sentiment classification models. In conclusion, the evaluation results reaffirm the efficacy of SVM with SMOTE in sentiment analysis tasks, emphasizing its value in deciphering consumer sentiments towards marketed products with high accuracy and precision.

Based on the evaluation results of SVM performance without using SMOTE, it is evident that the model achieves a high accuracy rate, with a mean accuracy of 97.94% and a micro average of 97.94%. The confusion matrix illustrates the effective classification of negative and positive instances, with a precision of 98.07% and a recall of 99.86% for the positive class. Additionally, the model demonstrates a robust f-measure of 98.96% for the positive class. However, the AUC scores indicate a relatively lower performance, with optimistic, average, and pessimistic values ranging from 0.668 to 0.671 for the positive class. Despite the lower AUC scores, the model showcases exceptional precision, recall, and f-measure metrics, indicating its proficiency in accurately classifying positive instances. These findings underscore the reliability and efficacy of the SVM model without SMOTE in sentiment analysis tasks, particularly in accurately identifying positive sentiments towards marketed products. In conclusion, while the AUC scores may suggest room for improvement, the overall performance metrics highlight the effectiveness of the SVM model without SMOTE in sentiment classification.

### Social Network Analysis of the Content Reviews

Based on the results of Social Network Analysis (SNA) implementation for the "who replies to whom" category, it is evident that the network exhibits a Diameter of 4, indicating the maximum distance between any two nodes within the network. Additionally, the Density, which represents the proportion of actual connections to possible connections, is calculated at 0.000266, suggesting a sparse network structure. The Reciprocity value of 0.000000 indicates a lack of mutual connections between nodes, while the Centralization score of 0.001468 suggests a relatively low degree of concentration of connections around a central node. Furthermore, the high Modularity value 0.999400 signifies a strong network division into distinct communities or modules. This comprehensive analysis of SNA metrics offers valuable insights into the structural characteristics and dynamics of the network, providing a foundation for further exploration and interpretation of communication patterns and relationships within the examined dataset.

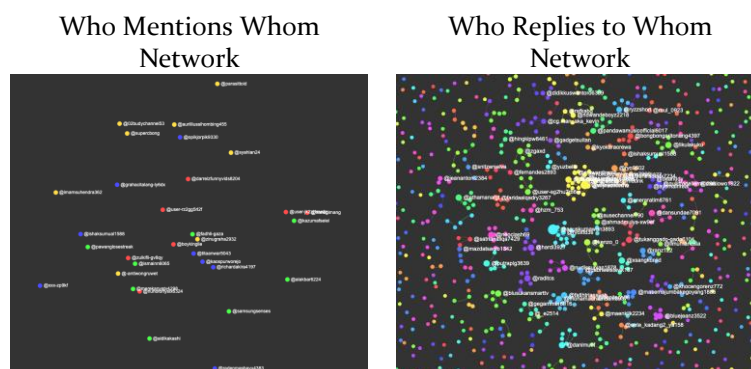


Figure 9. Social Network Analysis(Netlytic)

Based on the results of the implementation of Social Network Analysis (SNA) for the "who mentions whom" category, it is observed that the network exhibits a Diameter of 0, indicating that all nodes in the network are connected. The Density of the network, representing the proportion of actual connections to possible connections, is calculated at 0.000248, suggesting a sparse network structure with relatively few connections. The Reciprocity value is undefined (NaN), indicating the absence of mutual connections between nodes in this category. The Centralization score is calculated at 0.000000, suggesting an even distribution of connections among nodes without a central node exerting significant influence. Furthermore, the high Modularity value of 0.999800 indicates a strong network division into distinct communities or modules. This thorough analysis of SNA metrics provides valuable insights into the structural characteristics and dynamics of the network, laying the groundwork for deeper exploration and interpretation of communication patterns and relationships within the analyzed dataset.

#### 4. CONCLUSION

In conclusion, the toxicity analysis, sentiment classification, and Social Network Analysis (SNA) have been assessed through various metrics, providing a comprehensive evaluation of their performance. In toxicity analysis, the metrics indicate the model's effectiveness in identifying toxic language, with precision, recall, and f-measure scores reflecting its capability to discern instances of toxicity, severe toxicity, profanity, identity attacks, insults, and threats. The numerical values, such as Toxicity at 0.06194 and Severe Toxicity at 0.00730, help quantify the prevalence of these elements within the dataset. In sentiment classification, the model achieves an impressive accuracy of 97.94% with a micro-average of 97.94%. The confusion matrix highlights the model's ability to classify negative and positive instances, exhibiting a precision of 98.07% and a recall of 99.86% for the positive class. The robust f-measure of 98.96% further underscores the model's performance. However, AUC scores suggest a relatively lower performance, with optimistic, average, and pessimistic values ranging from 0.668 to 0.671 for the positive class. Finally, in Social Network Analysis (SNA), network characteristics like diameter, density, reciprocity, centralization, and modularity provide insights into the network structure. The density of 0.000266 suggests a sparse network, while the high modularity value of 0.999400 indicates strong community divisions. By considering these metrics collectively, stakeholders can make informed decisions for refining models and strategies in handling toxicity, sentiment, and network dynamics within digital spaces.

#### ACKNOWLEDGEMENTS

I sincerely thank the Faculty of Business Administration and Communication at the Atma Jaya Catholic University of Indonesia and the Research and Community Service Institute (LPPM).

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