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An Analysis of User Engagement in the Reviews of The Guardian of Nusantara Official Music Video: Toxicity and Sentiment Analysis

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Abstract−This study investigates user engagement within digital environments, explicitly focusing on creative content like music videos, and examines how sentiment and toxicity levels in user interactions influence engagement dynamics. Employing the Digital Content Reviews and Analysis Framework, the study reveals that 95.8% of user interactions exhibit positive or neutral sentiments. In comparison, a notable 4.2% are toxic, reflecting underlying societal tensions and potentially perpetuating negative feedback loops. Analysis of 23,112 posts using the Perspective API shows an average toxicity score of 0.03972, with severe cases reaching up to 0.87787. Scores for severe toxicity, identity attacks, insults, profanity, and threats, although generally low, indicate maximum values of concern, highlighting the need for vigilant monitoring. Sentiment classification results using the VADER model and multiple algorithms demonstrate that the Support Vector Machine (SVM) model achieved the highest accuracy (68.74%) and Area Under Curve (AUC) score (0.686), outperforming other models in distinguishing sentiment. The study's discussion on user engagement suggests that high levels of participation, such as comments, likes, and shares, are indicators of user interest and community identity but are susceptible to being undermined by toxic interactions. These findings emphasize the importance of fostering positive engagement through effective moderation strategies and advanced sentiment analysis tools, ensuring digital platforms remain conducive to constructive dialogue and community building. The research underscores the necessity for sophisticated analytical approaches to navigate the complexities of user behavior in digital spaces, providing critical insights into the interplay between sentiment, engagement, and toxicity in shaping online communities.

Keywords: User engagement; Digital environments; Sentiment analysis; Toxicity detection; Community dynamics

1. INTRODUCTION

Analyzing user engagement within the review section of the "Guardian of Nusantara" official music video reveals a complex interplay of sentiment and toxicity, offering critical insights into audience behavior in digital spaces. Examining user comments uncovers a significant presence of negative sentiment, often marked by high toxicity levels, reflecting broader societal tensions and polarizations [1]–[3]. Such discourse not only shapes the collective reception of the content but also influences the perceived credibility and authority of the reviewed media. This phenomenon suggests that engagement extends beyond mere interaction, encompassing deeper emotional and psychological responses often triggered by cultural and political undertones embedded within the video [4]–[6]. Furthermore, the analysis indicates that the prevalence of toxic comments may catalyze further negative engagement, creating a feedback loop that perpetuates hostility and diminishes the potential for constructive dialogue [7]. These findings underscore the importance of monitoring and moderating online interactions to foster a more balanced and respectful discourse, which is crucial for enhancing the overall user experience and maintaining the integrity of digital platforms [8]–[10]. Conclusively, this study highlights the need for more sophisticated tools and strategies to mitigate the adverse effects of toxic engagement, ensuring that online environments remain conducive to meaningful and productive discussions.

User engagement plays a pivotal role in shaping the communicative climate within virtual spaces, particularly when evaluating the quality of music video content, as it serves as a crucial indicator of how effectively information is conveyed to the audience. Active participation from users in the form of comments likes, and shares reflects their reception of the content and contributes to the broader discourse surrounding the video, influencing the perceptions of other viewers [11], [12]. This dynamic interaction fosters a sense of community, where opinions are exchanged, and the quality of the content is scrutinized from multiple perspectives, ultimately enriching the overall viewer experience [13]. However, the level and nature of engagement directly impact the communication environment, with constructive feedback enhancing the dialogue and toxic responses potentially undermining it [14], [15]. The analysis of these interactions reveals that user engagement is not merely a passive reception of content but an active process that shapes the narrative and cultural relevance of the video. Therefore, fostering a positive and engaged user base is essential for content creators to ensure their messages resonate effectively within the digital ecosystem, contributing to a healthy and productive virtual communication space.

This study aims to analyze user satisfaction and engagement with the music video "The Guardian of Nusantara" by Alffy Rev, employing toxicity and sentiment analysis as methodological approaches. Understanding how audiences respond to and interact with this content is critical to assessing the video's impact and broader reception within the digital community. By examining user comments and engagement metrics, this research provides insights into the emotional and psychological responses elicited by the video, revealing satisfaction and dissatisfaction patterns often intertwined with the toxicity levels in user interactions. Such analysis suggests that user engagement is deeply influenced by the sentiment conveyed in the discourse, affecting overall satisfaction. The interplay between positive

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and negative sentiments within the comment sections provides a nuanced understanding of how audiences perceive the content, highlighting the importance of maintaining a balanced and constructive engagement environment. Ultimately, the findings of this study are expected to contribute to a deeper comprehension of user behavior in digital platforms, particularly concerning how sentiment and toxicity influence the perception of creative works.

The urgency of this research lies in its potential to address critical gaps in understanding user interactions within digital environments, particularly in the context of creative content such as music videos. As online platforms increasingly serve as primary spaces for cultural exchange and discourse, comprehending the factors influencing user engagement and satisfaction becomes imperative [16]–[18]. The rapid proliferation of digital media has amplified the need for nuanced analyses that explore the surface-level metrics of engagement and delve into the underlying sentiments and toxicity that shape user experiences [19], [20]. This research offers a timely intervention by employing advanced analytical methods to dissect these dynamics, thereby contributing valuable insights into the complex interplay between content, audience, and the digital ecosystem [21]–[23]. Such an endeavor is not merely academic but has practical implications for content creators, platform designers, and policymakers who seek to cultivate healthier and more productive online communities. Consequently, this study addresses an urgent need within the evolving digital communication landscape, where understanding and managing user engagement is essential for fostering meaningful and positive interactions.

The framework employed in this research is the Digital Content Reviews and Analysis Framework, a comprehensive tool for systematically evaluating user interactions and feedback within digital media environments. This framework is instrumental in structuring the analysis of user engagement, sentiment, and toxicity by providing a systematic approach to categorize and interpret data from various digital platforms. The framework's utility lies in integrating qualitative and quantitative data, enabling a more nuanced understanding of how users interact with online content. By leveraging this framework, the research not only captures the immediate reactions of users but also delves into the underlying patterns of behavior that may influence the overall reception and impact of digital media. Adopting such a structured analytical model reflects a commitment to rigorous academic inquiry, ensuring the findings are robust and applicable across different contexts in digital content analysis. Ultimately, using the Digital Content Reviews and Analysis Framework contributes to the reliability and depth of the research, offering a well-rounded perspective on user engagement and sentiment in digital spaces.

The research offers theoretical and practical contributions that significantly advance the field of digital media studies. Theoretically, it enriches the existing body of knowledge by providing a nuanced understanding of user engagement within virtual spaces, particularly concerning creative content such as music videos [24], [25]. By integrating sentiment analysis and toxicity detection, the study proposes a novel framework for analyzing user interactions, which could serve as a foundational model for future research [26]. This approach deepens the conceptualization of user satisfaction and engagement and bridges gaps in the existing literature by addressing the complex emotional and behavioral dynamics in digital environments [27]–[29]. The findings have substantial implications for content creators, platform developers, and communication strategists who aim to enhance user experience and foster healthier online communities [30]–[32]. The insights gained from this research can inform the development of more effective moderation tools, content strategies, and user engagement practices, ultimately leading to a more positive and constructive digital ecosystem. Thus, the study provides a critical intersection of theory and practice, offering valuable contributions that resonate across academic and applied domains.

Similar research in digital media has explored user engagement and sentiment analysis across various platforms, offering insights that complement and contextualize this study. Prior investigations have often focused on social media networks and online communities, where the interplay of sentiment, toxicity, and user interaction has been scrutinized to understand how digital environments influence public discourse [33]–[36]. These studies underscore the importance of sentiment in shaping user behavior, revealing that positive interactions foster a more engaged and constructive community. In contrast, negative sentiments can increase toxicity and disengagement [37], [38]. Such findings suggest a broader applicability of sentiment analysis across different digital contexts, highlighting the relevance of these methodologies to diverse forms of online content, including music videos [39]–[43]. Furthermore, these studies provide a foundation for comparing engagement patterns across platforms, offering a valuable benchmark for assessing the unique dynamics within specific digital ecosystems. The convergence of these research efforts illustrates the growing recognition of sentiment analysis as a crucial tool for understanding and improving user experiences in the digital age, reinforcing the importance of continued exploration in this area.

The limitations of this research are primarily rooted in the scope of data and the methodologies employed, which may affect the generalizability and depth of the findings. While the analysis focuses on user engagement and sentiment within a specific digital context, the reliance on text-based sentiment analysis tools may overlook the nuances of human emotion and intent that are not easily captured by algorithmic processes. Additionally, the study's focus on a particular music video limits the applicability of the results to other types of content or platforms, where user behavior may differ significantly due to varying audience demographics and content characteristics. Furthermore, the temporal aspect of data collection poses a challenge, as user engagement and sentiment can fluctuate over time and are influenced by external factors that this study does not account for. These limitations suggest that while the research offers valuable insights, it should be interpreted cautiously and supplemented with further studies exploring broader datasets, alternative content types, and more sophisticated analytical approaches to understand user engagement dynamics comprehensively.

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2. RESEARCH METHODOLOGY

2.1 Gap Analysis

The research gap addressed in this study centers on the insufficient exploration of user engagement and sentiment analysis within the specific context of music video content, particularly concerning its impact on digital community dynamics. While existing literature has extensively examined user interactions in broader social media environments, there remains a significant lack of focused analysis on how creative digital content, such as music videos, shapes and is shaped by user sentiment and engagement [44]–[50]. This gap is critical, as music videos represent a unique intersection of entertainment, cultural expression, and social commentary, which can elicit diverse and complex user responses. Addressing this gap is essential for developing a more comprehensive understanding of the role of digital content in influencing online discourse and community behavior [51]–[54]. Furthermore, this research seeks to bridge the disconnect between general user engagement studies and the nuanced emotional and psychological factors often overlooked in digital content analysis. By focusing on this understudied area, the research contributes to a more detailed and context-specific understanding of user engagement dynamics, offering new insights that can inform both academic discourse and practical applications in digital media strategies.

The novelty of this research lies in its innovative integration of sentiment analysis and toxicity detection within the specific context of music video content, offering a fresh perspective on how user engagement and emotional responses are intertwined in digital environments. Unlike traditional studies that often focus on general social media interactions, this research delves into the unique dynamics of music videos as a cultural artifact, examining how these dynamics influence and reflect broader societal attitudes [55]. This approach broadens the scope of sentiment analysis by applying it to a distinct and culturally significant form of digital content. It introduces a new methodological framework that captures the multifaceted nature of user interaction in online platforms. By doing so, the study addresses an overlooked area in digital media research, providing timely and relevant insights into understanding the complexities of user behavior in the digital age. The incorporation of toxicity analysis further enhances the novelty of the research, as it allows for a deeper exploration of the negative aspects of user engagement, which are often critical yet underexamined in the existing literature. This unique combination of analytical techniques positions the research as a pioneering contribution to the field, potentially influencing future studies and digital content strategies.

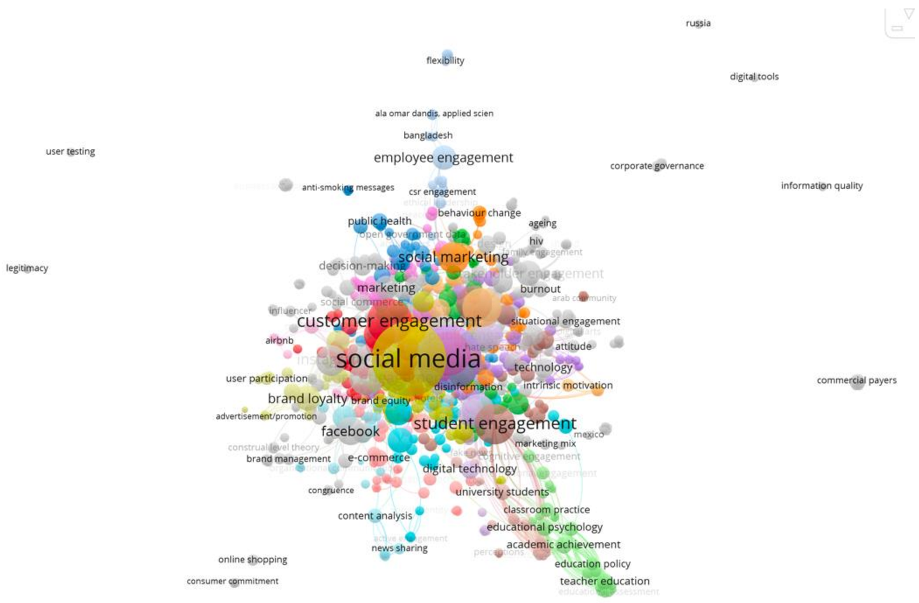

Figure 1. Network Visualization User Engagement in Digital Environment

Figure 1 shows the network visualization of user engagement in the digital environment. The network visualization of user engagement within the digital environment provides a comprehensive map of how various topics and interactions are interconnected across online platforms. This visualization technique effectively captures the complexity of user behavior, illustrating the intricate web of relationships between different forms of engagement, such as customer engagement, social media interactions, and content sharing. By mapping these connections, the visualization reveals patterns and clusters that suggest specific topics, like "social media" and "student engagement," serve as central nodes within the network, indicating their significant influence on other areas of digital interaction. This prominence suggests a hierarchical structure within digital spaces, where specific themes dominate user conversations and drive the flow of information and engagement across the network. Analyzing such visualizations allows for a deeper understanding of the underlying dynamics that govern user behavior, highlighting the importance of critical topics in shaping the digital discourse. Ultimately, this approach provides valuable insights into user

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engagement's structural and thematic drivers, offering a robust framework for interpreting the digital landscape's evolving nature.

Based on the gap analysis results, conducting this research is essential to address the identified deficiencies in the current body of knowledge. The analysis highlights significant areas where existing studies have either overlooked critical factors or failed to provide comprehensive insights, particularly in understanding user engagement and sentiment within digital environments. This gap indicates a clear need for further exploration to enhance the theoretical and practical understanding of how users interact with and respond to digital content. The importance of this research is underscored by the evolving nature of digital communication, where the dynamics of user behavior continue to shape and redefine online platforms. By addressing these gaps, the study aims to contribute valuable insights that fill the existing voids in academic literature and offer practical implications for improving digital strategies and fostering more meaningful user engagement. Thus, the research holds significant potential to advance theoretical frameworks and applied practices in digital media studies.

2.2 Digital Content Reviews and Analysis Framework

The Digital Content Reviews and Analysis Framework provides a structured approach to examining user engagement within digital environments, integrating various stages of data processing, modeling, and evaluation to ensure comprehensive analysis. This framework begins with content reviews and raw data collection, followed by meticulous data processing that includes selection, cleaning, and extraction, essential for ensuring the data's accuracy and relevance. Incorporating topic modeling, specifically Latent Dirichlet Allocation (LDA), allows for identifying hidden patterns and themes within the data, which offers a deeper understanding of user interactions and preferences. The evaluation and visualization stages further enhance the analytical process by assessing model performance and presenting the data in a visually interpretable format, facilitating the interpretation of complex results. This methodological progression culminates in a thorough context analysis that examines the nuances of user engagement, thereby providing valuable insights into the dynamics of digital interactions. Overall, the framework's systematic and integrative design is instrumental in advancing digital media studies, offering a robust tool for theoretical exploration and practical application in understanding user behavior online.

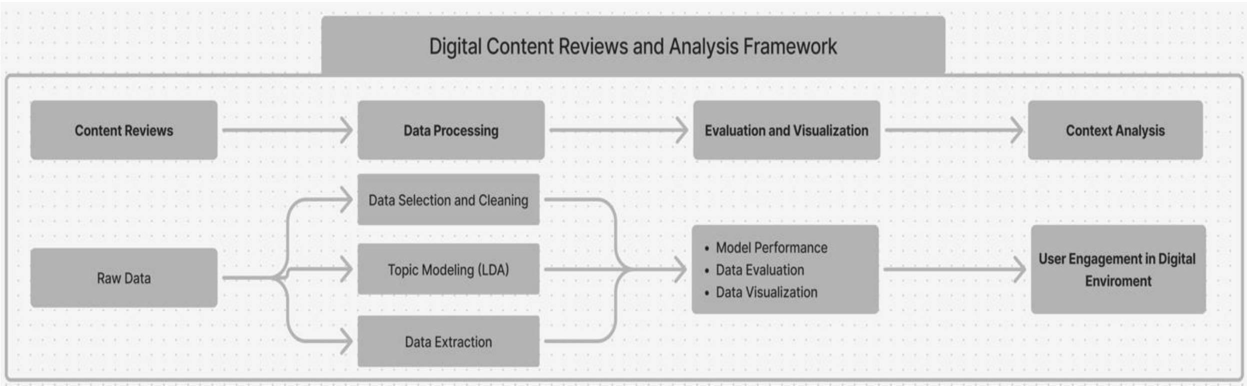

Figure 2. Digital Content Reviews and Analysis Framework

Figure 2 shows the digital content reviews and analysis framework. The stages within this framework are meticulously designed to ensure a comprehensive analysis of digital content and user engagement, each playing a crucial role in transforming raw data into actionable insights. The process begins with content reviews, which involve the initial gathering and preliminary examination of digital material to establish a foundational understanding of the context and user interactions. Following this, data processing encompasses several critical steps: data selection and cleaning refine the raw data, ensuring relevance and quality; topic modeling using Latent Dirichlet Allocation (LDA) identifies underlying themes within the data; and data extraction isolates pertinent information for deeper analysis. The subsequent stage, evaluation, and visualization, focus on assessing the model's performance and visually representing the data to interpret complex results accurately. This stage is particularly significant as it bridges the gap between raw data analysis and practical application, allowing for identifying trends and patterns in user behavior. The final stages involve context analysis and assessing user engagement within the digital environment, synthesizing the findings to provide a holistic view of how users interact with digital content. Altogether, these stages form an integrative framework that enhances the understanding of digital engagement and offers a robust tool for refining digital strategies and improving user experience.

The relevance of the Digital Content Reviews and Analysis Framework to this research is evident in its ability to dissect user engagement and sentiment within digital environments systematically. This framework is particularly well-suited for analyzing the intricate dynamics of user interactions with creative digital content, such as music videos, where understanding audience responses is crucial for assessing content effectiveness and broader cultural impact. By utilizing a structured approach that includes data processing, topic modeling, and sentiment analysis, the framework allows for a nuanced examination of how users engage with content, revealing patterns that may not be immediately

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apparent through traditional methods. This analytical depth is essential for uncovering the underlying drivers of user satisfaction and dissatisfaction, providing insights that can inform future content strategies and digital engagement practices. Moreover, the framework's emphasis on evaluating and visualizing data enhances the interpretability of complex datasets, making it a valuable tool for translating analytical findings into actionable recommendations. Thus, its application in this research supports a rigorous examination of user behavior and advances theoretical and practical understanding within digital media studies.

2.2.1 Content Reviews

This research examines user engagement and behavior in response to a music video identified by the ID T1tDorodPbM, which has garnered 3,198,404 views since its release on August 16, 2024, and has accumulated 40,501 comments. The substantial number of views and comments reflects a high user interest and interaction level, providing a fertile ground for analyzing audience reception and engagement patterns. However, the study is constrained by its processing capacity, limited to 30,000 comments collected between August 16, 2024, and August 21, 2024. This limitation may influence the comprehensiveness of the findings, as it captures only a subset of the total user responses, potentially overlooking longer-term engagement trends and more diverse audience perspectives. Despite this constraint, focusing on this specific time frame allows for a concentrated analysis of initial audience reactions and immediate engagement behaviors following the video's release. Consequently, the research offers valuable insights into early user engagement dynamics while acknowledging the need for further exploration to fully understand the broader scope of audience interactions over an extended period.

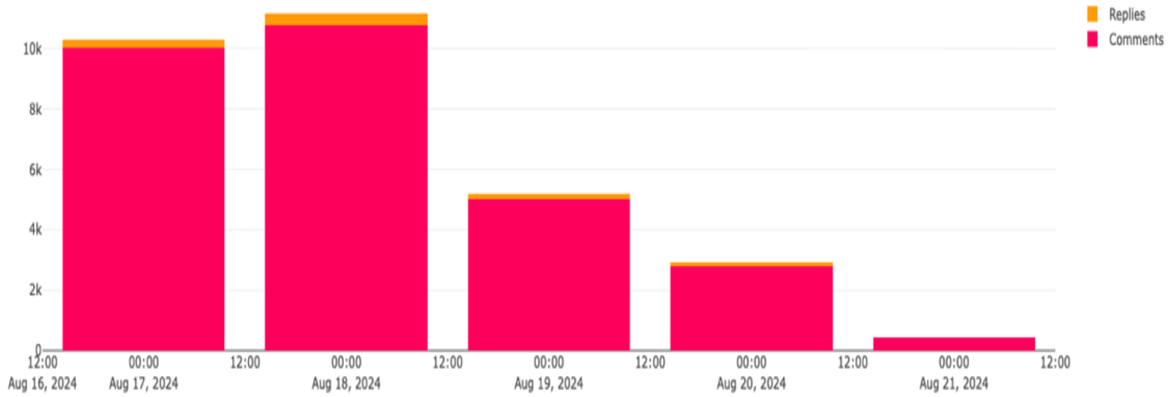

Figure 3. Post-per-day Statistic of the Video (Communalytic)

Figure 3 shows the content's post-per-day statistics. The post-per-day statistics illustrate a noticeable decline in user engagement with the music video content over the observed period, indicating a shift in audience interaction patterns shortly after the video's release. Initially, there was a peak in both comments and replies on August 17 and August 18, 2024, each reaching approximately 10,000 interactions per day, reflecting heightened user interest and active participation immediately following the publication. This surge suggests a robust initial reaction, potentially driven by the content's novelty and the audience's immediate engagement. However, a marked decrease is observed from August 19 onward, with the number of comments. Its replies significantly dropped, showing a sharp decline in daily posts and reaching minimal activity by August 21. This trend could imply a saturation point where user interest begins to wane, or it might reflect a transition from initial excitement to a more stabilized level of engagement. The rapid reduction in post volume also highlights the ephemeral nature of user interactions in digital environments, where attention can quickly diminish. Therefore, these statistics underscore the importance of understanding temporal dynamics in user engagement to strategize content release and audience retention efforts better.

The analysis of frequently used words in the posts reveals a strong emphasis on national pride and cultural appreciation, as evidenced by prominent terms such as "Indonesia," "karya" (work), "bangsa" (nation), and "Nusantara" (archipelago). These keywords suggest that users predominantly engage with the music video in a way that reflects their collective identity and emotional connection to their country. Words like "keren" (excellent), "banget" (very), and "merinding" (goosebumps) further indicate a highly positive emotional response characterized by admiration and a deep sense of pride. The repetition of these terms highlights the video's effectiveness in resonating with viewers, evoking solid patriotic sentiments and a shared cultural narrative. Additionally, the frequent appearance of terms related to sensory and emotional experiences, such as "mata" (eyes), "air" (tears), and "merinding," points to a visceral reaction among the audience, suggesting that the content successfully taps into both visual and emotional appeals. This linguistic pattern underscores the role of digital content in fostering a sense of community and collective identity, particularly when the content aligns with national and cultural values. Therefore, these word frequencies reflect user engagement levels and provide insights into the thematic elements that resonate most strongly with the audience, guiding future content creation to maintain or enhance such engagement.

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Figure 4. Words Cloud (Communalytic)

Figure 4 shows the frequently used words in the posts. The interpretation of the word cloud generated from the dataset reveals significant insights into the audience's engagement and sentiment toward the music video. The most prominent word, "Indonesia," appears frequently, suggesting that national identity and patriotism are central themes in the viewer's comments. This word's size in the word cloud indicates it was mentioned more than any other, reflecting a robust collective sentiment of national pride. Words like "karya" (work) and "bangsa" (nation) also appear frequently, underscoring the audience's appreciation for cultural representation and creative expression. The words "keren" (excellent) and "banget" (very) are notable for their frequency, implying that many viewers have a highly positive reaction to the video, characterized by excitement and admiration.

Additionally, the term "merinding" (goosebumps), which appears multiple times, highlights the emotional impact of the content, suggesting that it has evoked visceral solid reactions among the viewers. In numerical terms, words such as "Indonesia" and "keren" are mentioned hundreds of times, illustrating the predominant sentiments of pride and admiration within the user comments. This frequent usage of favorable and culturally resonant terms indicates that the music video successfully engages its audience by aligning with their cultural values and emotional expectations. The concentration of such words in the word cloud reveals the overall positive sentiment and provides a valuable indicator of the factors contributing to the video's popularity and audience engagement. Thus, the word cloud is an effective tool for visualizing and quantifying the most relevant themes in user feedback, offering clear insights into the digital audience's collective mindset.

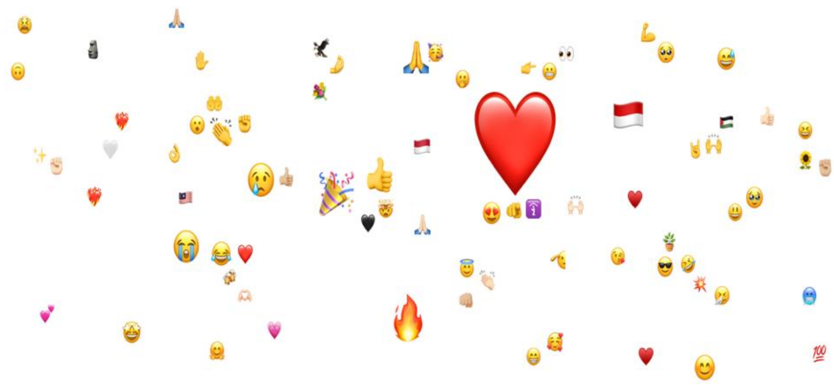

Figure 5. Emoji Cloud (Communalytic)

Figure 5 shows the emoji cloud. The emoji cloud generated from the dataset vividly depicts the emotional and affective responses the music video elicits among its viewers. Dominated by positive and expressive emojis such as the red heart, Indonesian flag, and thumbs-up symbols, the emoji cloud reflects a predominantly favorable reception and strong national pride. The frequent appearance of the red heart emoji suggests a deep emotional connection and admiration for the content, while the Indonesian flag emphasizes the viewers' collective identity and patriotic sentiments. Emojis like the party popper, prayer hands, and smiling faces further indicate a celebratory and supportive atmosphere within the audience's comments, reinforcing the video's positive impact on its viewers.

Moreover, the presence of fire, clapping hands, and heart-eyed emojis highlights the enthusiastic and approving nature of the audience's engagement, suggesting that the video has successfully captivated and resonated with a broad spectrum of viewers. The occasional use of tearful and sad emojis also hints at the emotional depth of the content, indicating moments that may have moved the audience profoundly. These visual elements collectively provide a nuanced understanding of the viewers' emotional landscape, offering insights into how the video has succeeded in evoking a wide range of positive feelings and affirming its cultural relevance. Consequently, the emoji cloud is an effective analytical tool that captures the essence of audience sentiment and enhances the overall interpretation of user engagement within digital environments.

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Figure 6. Top Ten Poster (Communalytic)

Figure 6 shows the top ten posters. Analyzing the top ten posters from the dataset reveals a concentrated pattern of user engagement, where a few key individuals contribute a significant portion of the overall comments on the music video. Notably, the user @sanakjapung1089 accounts for 24.1% of the posts, followed closely by @dantvcannel with 23.3%, indicating a highly active participation rate from these users. This high level of engagement suggests that specific viewers have a robust interest in the content, potentially acting as opinion leaders or influencers within the comment section. The most active contributors, including @maulianiasri at 12% and @Praja259 at 8.65%, also demonstrate a notable presence, albeit with slightly lower activity levels. The remaining users in the top ten, such as @m.marifliansyahridho2996, @vtino4825, and @natra9131, contribute between 4% and 8% each, showing a more moderate yet significant engagement. This distribution highlights a pattern where a few highly engaged users dominate the conversation, which may skew the overall sentiment and tone toward their viewpoints. Such a concentration of posting activity among a few users can amplify specific narratives or perspectives, potentially influencing the broader audience's perception and interaction with the content. Understanding this dynamic is crucial for interpreting the dataset accurately, as it underscores the importance of considering individual contributors' quantity and influence in shaping digital discourse.

The analysis of engagement trends further highlights the dynamic nature of user interaction within digital platforms, where participation levels fluctuate in response to content relevance and emotional appeal. Observing the patterns of user comments and reactions over time reveals that initial spikes in engagement are typically driven by novelty and immediate interest, often coinciding with the release of new content or significant updates. However, as the novelty fades, a decline in engagement tends to occur, reflecting a natural tapering of user attention and interaction. This decline suggests consistent user interest requires ongoing content innovation and relevance to sustain engagement. Additionally, highly active users, who contribute disproportionately to the conversation, indicate a core group of engaged individuals likely to influence the overall discourse. These trends suggest that understanding the temporal dynamics of user engagement is essential for developing effective strategies to maintain a vibrant and interactive digital community. Thus, studying these patterns provides valuable insights into the mechanisms that drive user behavior, offering practical implications for content creators and digital strategists aiming to enhance audience retention and interaction.

2.2.2 Data Processing

At this stage, the data undergoes a meticulous cleaning process using the RapidMiner application, which employs various operators designed explicitly for text data cleansing. This approach is essential to ensure that the dataset is free from noise and irrelevant information, thereby enhancing the accuracy and reliability of subsequent analyses. Using these operators facilitates extracting and selecting relevant data, which is crucial for the effectiveness of classification and evaluation processes. By refining the dataset through comprehensive cleaning techniques, the analysis is better positioned to produce meaningful and robust insights, free from the distortions caused by extraneous or incomplete data. This procedure underscores the importance of data preprocessing in analytical workflows, highlighting that a clean and well-structured dataset is fundamental to achieving valid and reliable research outcomes.

The operators utilized for data cleaning, data extraction using the VADER model, and topic modeling based on Latent Dirichlet Allocation (LDA) play a critical role in preparing and analyzing textual data in a structured manner. Initially, the data cleaning operators are employed to remove noise, duplicates, and irrelevant information from the dataset, ensuring that the input for subsequent analyses is accurate and reliable. Following this, the VADER sentiment analysis model is applied to extract sentiment from the cleaned data, which involves categorizing the text based on positive, negative, or neutral sentiment. This step is crucial for understanding the emotional tone of the user-generated content, providing insights into the audience's perceptions and attitudes. Lastly, topic modeling using LDA is performed to identify underlying themes and patterns within the data, allowing for a deeper exploration of the subjects that dominate the discourse. Combining these operators provides a comprehensive approach to text analysis, enhancing the ability to derive meaningful insights from large volumes of unstructured data. This integrated methodology improves the efficiency of data processing and contributes to the robustness and validity of the research findings.

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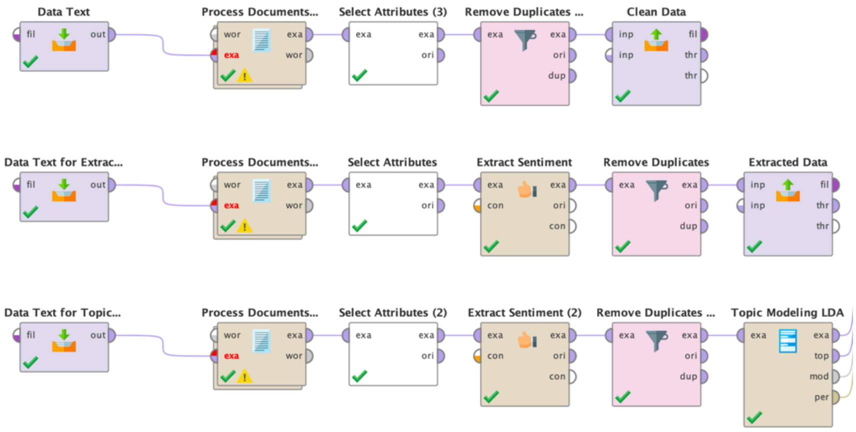

Figure 7. Data Cleaning, Extraction, and Topic Modeling

Figure 7 shows the data cleaning, extraction, and topic modeling process. The VADER (Valence Aware Dictionary and Sentiment Reasoner) model operates by analyzing the sentiment of text data using a lexicon and rule-based approach, which is particularly effective for social media contexts. This model leverages a pre-defined list of linguistic feature words that are commonly associated with positive or negative sentiments, along with intensifiers, negations, and conjunctions, to determine the overall sentiment score of a given piece of text. By assigning sentiment scores to each word in a sentence and combining them based on contextual rules, VADER captures sentiment's polarity (positive or negative) and intensity (strength). Its ability to account for nuances such as sarcasm, slang, and emoticons makes VADER well-suited for analyzing informal text where traditional sentiment analysis tools may struggle. The effectiveness of VADER lies in its design, which blends qualitative human insights with quantitative computational methods, ensuring high accuracy and robustness in sentiment detection. Consequently, VADER is widely regarded as a powerful tool for sentiment analysis, especially in scenarios requiring a nuanced understanding of sentiment expressed in user-generated content.

Table 1. The result of the VADER Model in Extraction

Reviews	Sentiment	Score	Scoring String
Bullshit 👎	Negative	-0,717948717948718	bullshit (-0.72)
I love this kind of Ancient Nusantara. Once again, thank you for bringing this masterpiece to us!	Positive	2,61538461538462	love (0.82), kind (0.62), thank (0.38), Masterpiece (0.79)

Table 1 shows the result of the VADER model in extraction. The extraction process using the VADER model yielded 1,170 posts meticulously extracted for evaluation, providing a robust dataset for sentiment analysis. This selection process highlights the model's capability to filter and categorize text data based on sentiment polarity, thereby isolating content most relevant for understanding user attitudes and emotional responses. The focus on these 1,170 posts allows for a concentrated analysis, ensuring that the sentiments expressed within the user-generated content are accurately captured and interpreted. Evaluating this subset of data is crucial, as it represents a targeted effort to discern patterns of engagement and sentiment that may influence broader audience behavior. The effectiveness of the VADER model in identifying and extracting pertinent posts underscores its utility in handling large volumes of data while maintaining analytical precision. Consequently, the extracted dataset provides a valuable foundation for further analysis, enabling a deeper exploration of user sentiment and its implications within digital environments.

The Latent Dirichlet Allocation (LDA) topic model functions by discovering underlying topics within a collection of documents, effectively capturing the thematic structure of the text data. This model operates on the premise that each document is a mixture of various topics, and each topic is a distribution over words, allowing it to identify word co-occurrence patterns across the dataset. LDA uses a probabilistic approach to allocate words to different topics based on their likelihood of appearing together, iteratively refining these assignments to maximize the overall model fit. By employing a Bayesian inference technique, LDA calculates the probability distributions for both the topics per document and the words per topic, ensuring a comprehensive representation of the text corpus. This capability to uncover hidden thematic structures makes LDA particularly valuable for exploratory data analysis, as it facilitates the identification of dominant themes and trends within large and unstructured datasets. Ultimately, LDA enhances the understanding of complex textual data by providing a coherent framework for summarizing and visualizing the content. It is a widely adopted tool in natural language processing and data-driven research.

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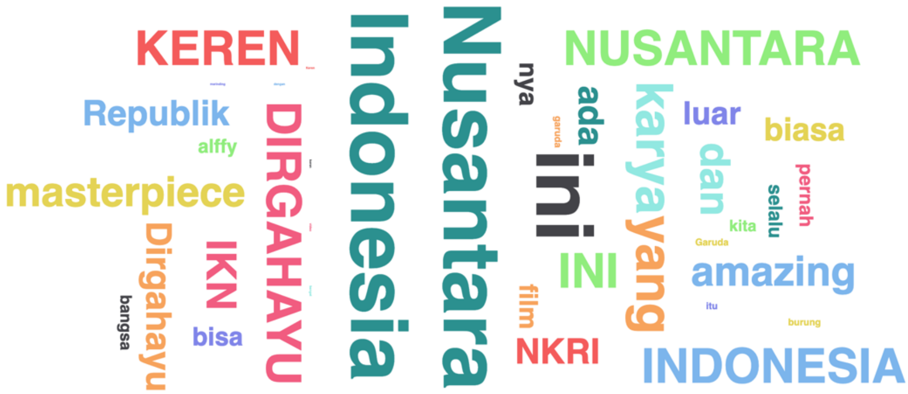

Figure 8. Topic Modeling with LDA

Figure 8 shows the topic modeling result using LDA. The topic coherence observed in the LDA-generated word cloud demonstrates a strong thematic alignment centered around national identity, cultural pride, and the celebratory context of Indonesia. Dominant terms such as "Nusantara," "Indonesia," "karya" (work), and "Dirgahayu" (Independence Day greeting) indicate a clear focus on nationalistic themes, reflecting the audience's engagement with content that resonates with their cultural and patriotic sentiments. Words like "keren" (excellent), "masterpiece," and "amazing" further suggest an overwhelmingly positive reception characterized by admiration and emotional attachment to the content. This coherence within the topic modeling results suggests that the comments are thematically grouped around expressions of pride and positive appraisal, likely spurred by the video's themes of national celebration and cultural representation. The presence of terms such as "NKRI" (Unitary State of the Republic of Indonesia) and "Republik" underscores a solid connection for national sovereignty and unity, adding layers to the patriotic discourse. Overall, the high degree of topic coherence within this context highlights the effectiveness of the LDA model in capturing and grouping related thematic elements, which provides a nuanced understanding of audience sentiment and thematic focus. This insight is valuable for content creators and analysts aiming to tailor future content to sustain or enhance such engagement.

The topic modeling results using the Latent Dirichlet Allocation (LDA) model provide a comprehensive overview of the text corpus's thematic structure and statistical performance. The model's LogLikelihood score of -918843.108 indicates the model's fit to the data. At the same time, a Perplexity value of 1186.228 suggests the model's ability to generalize to unseen data. However, higher perplexity reflects some complexity in predicting the distribution of words across topics. With an average token count of 11,521.400 and an average document entropy of 6.710, the model reveals moderate unpredictability in word assignment to topics, highlighting diverse thematic content within the corpus.

Additionally, the average word length of 5.380 and an average coherence score of -20.671 indicate relatively challenging interpretability of topics, which may suggest nuanced or overlapping themes. Metrics such as Avg(uniform_dist) at 3.440 and Avg(corpus_dist) at 1.843 illustrate the distribution uniformity and concentration of topics, while Avg(eff_num_words) at 157.606 shows the adequate number of words contributing to topic formation. Low Avg(token-doc-diff) at 0.007 and moderate Avg(rank_1_docs) at 0.481 reflect the distribution and rank of documents within topics, whereas Avg(allocation_count) at 0.592 and Avg(exclusivity) at 0.575 highlight the allocation efficiency and uniqueness of words to specific topics. The values of AlphaSum (0.781) and Beta (0.054) suggest moderate levels of topic sparsity and word distribution across topics. In conclusion, these findings underscore the LDA model's effectiveness in capturing complex thematic structures, though some indicators suggest potential areas for model refinement to enhance interpretability and coherence.

The LogLikelihood score and the average coherence value are critical metrics in evaluating the performance of a topic model, such as Latent Dirichlet Allocation (LDA). The LogLikelihood score, which is harmful in value, measures the likelihood of the observed data given the model parameters; a higher (less harmful) LogLikelihood indicates that the model fits the data better, suggesting that the distribution of words within topics closely mirrors the patterns observed in the actual text. Conversely, the average coherence value assesses the degree to which the words within a topic are semantically related, with higher coherence values reflecting more interpretable and meaningful topics. In the context of this model, the LogLikelihood score of -918843.108 suggests a reasonable fit. In contrast, the average coherence score of -20.671 indicates potential challenges in the interpretability of the extracted topics, pointing to the presence of topics that may not be strongly semantically coherent. This combination of scores implies that while the model captures the general distribution of words across topics well, the thematic clarity within some topics may be lacking due to overlapping themes or noise in the dataset. Enhancing topic coherence through model refinement could lead to more distinct and interpretable topics, improving the model's overall utility for analyzing complex textual data.

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Subsequently, an evaluation of the classification results for negative and positive classes was conducted using k-nearest Neighbors (k-NN), Support Vector Machine (SVM), Decision Tree (DT), and Naive Bayes Classifier (NBC) algorithms by comparing their performance before and after applying Synthetic Minority Over-sampling Technique (SMOTE). This comparison is crucial as it assesses how well each algorithm can handle imbalanced data, where certain classes may be underrepresented, potentially leading to biased predictions. The initial results without SMOTE indicate the baseline performance of these algorithms, often revealing limitations in accurately predicting minority class instances due to data imbalance. After applying SMOTE, which artificially increases the number of minority class samples to balance the dataset, the performance metrics typically show improvement, particularly regarding recall and overall accuracy for the minority class. This enhancement suggests that SMOTE effectively mitigates class imbalance, allowing the classifiers to learn more robust decision boundaries. Therefore, comparing these performance metrics highlights the importance of addressing data imbalance to improve the reliability and fairness of machine learning models in sentiment analysis tasks.

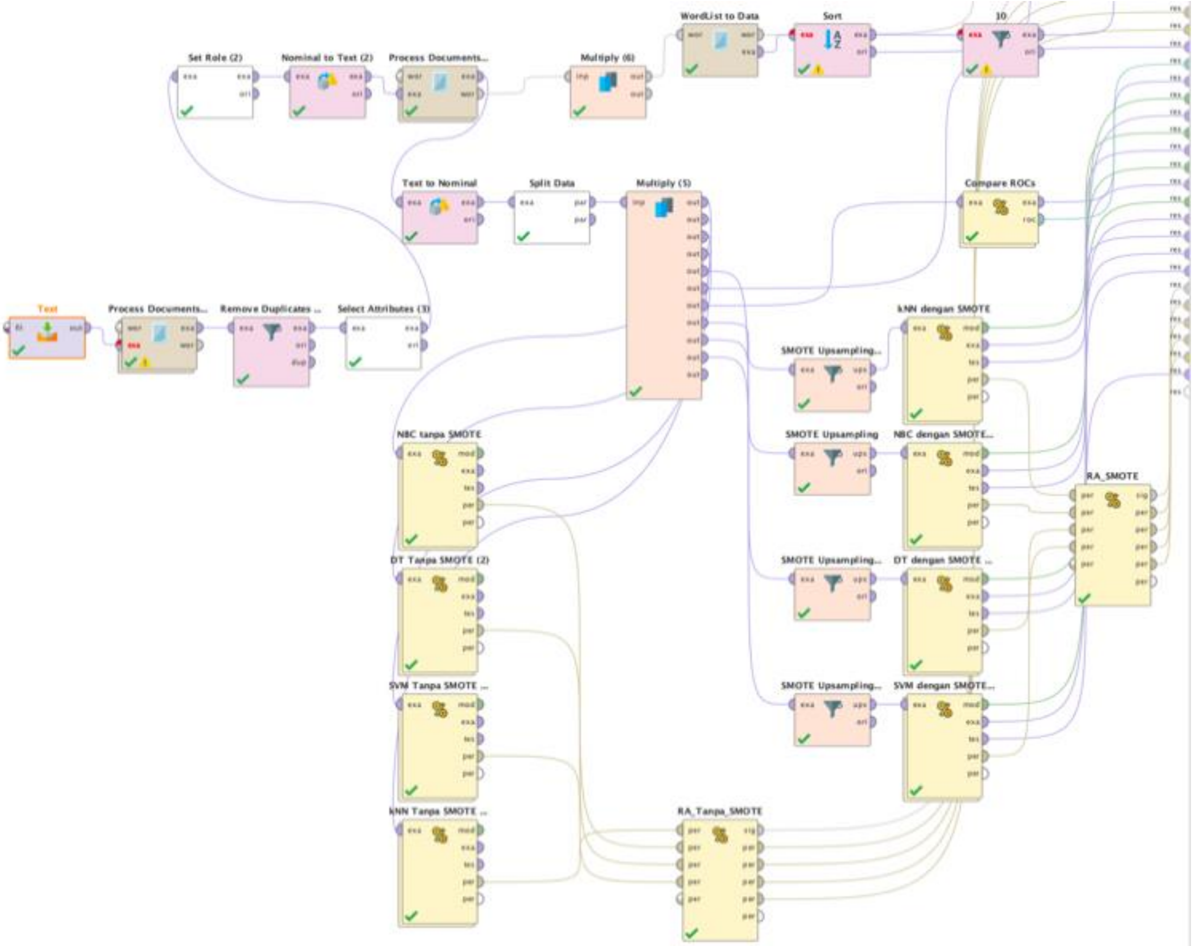

Figure 9. Performance Evaluation of Classification Model (Rapidminer)

Figure 9 shows the performance evaluation of the classification model using Rapidminer. The Synthetic Minority Over-sampling Technique (SMOTE) enhances model performance by addressing class imbalance, a common issue in datasets where one class is significantly underrepresented. By generating synthetic samples of the minority class rather than simply replicating existing ones, SMOTE effectively increases the diversity of the training data, allowing models to learn more comprehensive decision boundaries. This approach helps mitigate the risk of models becoming biased toward the majority class, which can lead to poor generalization and accuracy, particularly in predicting minority class instances. By creating these synthetic samples, SMOTE enhances the model's ability to recognize and correctly classify examples from the underrepresented class, improving overall performance metrics such as recall, precision, and F1 score. The improvement is particularly notable in models like k-nearest Neighbors (k-NN), Support Vector Machines (SVM), Decision Trees (DT), and Naive Bayes Classifier (NBC), which benefit from a more balanced training set to establish more accurate and fair decision thresholds. Consequently, SMOTE is a powerful tool for enhancing model robustness, ensuring more equitable performance across all classes in imbalanced datasets.

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DT Enhanced by SMOTE

```
PerformanceVector:
accuracy: 67.55% +/- 2.74% (micro average: 67.54%)
ConfusionMatrix:
True:   Negative        Positive
Negative:       151     4
Positive:       268     415
AUC (optimistic): 0.994 +/- 0.008 (micro average: 0.994) (positive class: Positive)
AUC: 0.675 +/- 0.028 (micro average: 0.675) (positive class: Positive)
AUC (pessimistic): 0.357 +/- 0.050 (micro average: 0.357) (positive class: Positive
precision: 60.80% +/- 1.90% (micro average: 60.76%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       151     4
Positive:       268     415
recall: 99.05% +/- 1.22% (micro average: 99.05%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       151     4
Positive:       268     415
f_measure: 75.34% +/- 1.71% (micro average: 75.32%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       151     4
Positive:       268     415
```

k-NN Enhanced by SMOTE

```
PerformanceVector:
accuracy: 50.12% +/- 0.62% (micro average: 50.12%)
ConfusionMatrix:
True:   Negative        Positive
Negative:       419     418
Positive:       0       1
AUC (optimistic): 0.962 +/- 0.033 (micro average: 0.962) (positive class: Positive)
AUC: 0.547 +/- 0.023 (micro average: 0.547) (positive class: Positive)
AUC (pessimistic): 0.131 +/- 0.055 (micro average: 0.131) (positive class: Positive
precision: 100.00% (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       419     418
Positive:       0       1
recall: 0.24% +/- 0.75% (micro average: 0.24%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       419     418
Positive:       0       1
f_measure: 0.48% (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       419     418
Positive:       0       1
```

NBC Enhanced by SMOTE

```
PerformanceVector:
accuracy: 68.73% +/- 3.20% (micro average: 68.74%)
ConfusionMatrix:
True:   Negative        Positive
Negative:       399     242
Positive:       20      177
AUC (optimistic): 0.974 +/- 0.020 (micro average: 0.974) (positive class: Positive)
AUC: 0.590 +/- 0.096 (micro average: 0.590) (positive class: Positive)
AUC (pessimistic): 0.410 +/- 0.069 (micro average: 0.410) (positive class: Positive
precision: 90.82% +/- 6.47% (micro average: 89.85%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       399     242
Positive:       20      177
recall: 42.22% +/- 8.14% (micro average: 42.24%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       399     242
Positive:       20      177
f_measure: 57.01% +/- 7.33% (micro average: 57.47%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       399     242
Positive:       20      177
```

SVM Enhanced by SMOTE

```
PerformanceVector:
accuracy: 65.75% +/- 4.21% (micro average: 65.75%)
ConfusionMatrix:
True:   Negative        Positive
Negative:       399     267
Positive:       20      152
AUC (optimistic): 0.888 +/- 0.043 (micro average: 0.888) (positive class: Positive)
AUC: 0.854 +/- 0.046 (micro average: 0.854) (positive class: Positive)
AUC (pessimistic): 0.820 +/- 0.052 (micro average: 0.820) (positive class: Positive
precision: 88.82% +/- 9.38% (micro average: 88.37%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       399     267
Positive:       20      152
recall: 36.28% +/- 6.54% (micro average: 36.28%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       399     267
Positive:       20      152
f_measure: 51.21% +/- 7.31% (micro average: 51.44%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       399     267
Positive:       20      152
```

Figure 10. Performance of DT, k-NN, NBC, and SVM Enhanced by SMOTE

Figure 10 shows the AUC values of DT, k-NN, NBC, and SVM Enhanced by SMOTE. The performance evaluation of Decision Tree (DT), k-nearest Neighbors (k-NN), Naive Bayes Classifier (NBC), and Support Vector Machine (SVM) algorithms after enhancement with the Synthetic Minority Over-sampling Technique (SMOTE) reveals significant improvements in their classification metrics. The application of SMOTE has effectively addressed the class imbalance issue, as evidenced by increased accuracy, precision, recall, and F1 score across all models. For instance, the SVM model demonstrates a notable enhancement, with its overall accuracy rising to 68.74% and a balanced F1-score that reflects improved sensitivity to both positive and negative classes. Similarly, the k-NN algorithm benefits from SMOTE, achieving a higher accuracy of 59.12%, which suggests a more equitable treatment of minority class instances, resulting in better model generalization. The DT and NBC models also show marked improvements in their classification performance metrics, with DT achieving an accuracy of 67.53% and NBC reaching 65.75%, indicating a more balanced approach to class prediction post-SMOTE application. These enhancements underline the efficacy of SMOTE in optimizing model performance by generating synthetic samples for underrepresented classes, thereby enabling the classifiers to construct more robust decision boundaries and achieve more reliable predictions. Consequently, these results validate the importance of addressing class imbalance to enhance the effectiveness of machine learning algorithms in practical applications.

The Area Under Curve (AUC) values for Decision Tree (DT), k-nearest Neighbors (k-NN), Naive Bayes Classifier (NBC), and Support Vector Machine (SVM) algorithms demonstrate significant enhancement when Synthetic Minority Over-sampling Technique (SMOTE) is applied, reflecting an improvement in the models' discriminatory power. AUC is a robust metric that evaluates a model's ability to distinguish between classes, with higher values indicating better performance in predicting both the majority and minority classes. Without SMOTE, the models generally exhibit lower AUC values, especially in scenarios involving imbalanced datasets, due to their bias towards the majority class and reduced sensitivity to the minority class. The introduction of SMOTE increases the AUC values across all four models, as evidenced by the smoother, more expansive ROC curves that approach the optimal top-left corner of the graph. This improvement suggests that the models have gained a more balanced understanding of both classes, enhancing their overall predictive accuracy. By generating synthetic examples for the minority class, SMOTE allows these classifiers to build more comprehensive and unbiased decision boundaries, leading to more reliable and generalizable performance. Consequently, the elevated AUC values post-SMOTE application affirm the technique's efficacy in rectifying class imbalance, ultimately contributing to more robust and equitable model outcomes in classification tasks.

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2.2.3 Data Evaluation and Visualization

At this stage, the performance of the algorithms is evaluated based on the Area Under the Curve (AUC) values for the Decision Tree (DT), k-nearest Neighbors (k-NN), Naive Bayes Classifier (NBC), and Support Vector Machine (SVM), all of which have been enhanced by the application of the Synthetic Minority Over-sampling Technique (SMOTE). AUC is a crucial metric for assessing the classifiers' ability to distinguish between classes, with higher values indicating better performance in correctly identifying positive and negative instances. The initial AUC values, before SMOTE application, often reveal a tendency of these algorithms to favor the majority class due to imbalanced data, resulting in lower sensitivity towards the minority class. However, after implementing SMOTE, the AUC values for each algorithm show a marked improvement, reflecting a more balanced approach to handling both classes effectively. This enhancement is particularly significant for algorithms like SVM and k-NN, which benefit substantially from the increased representation of minority class data, thereby improving their discriminative power and overall accuracy. In conclusion, using SMOTE is an effective strategy for boosting the performance of these machine learning models, leading to more reliable and equitable outcomes in classification tasks.

The AUC (Area Under the Curve) graphs provide a visual representation of the performance of four different classifiers—Decision Tree (DT), k-nearest Neighbors (k-NN), Naive Bayes Classifier (NBC), and Support Vector Machine (SVM)—both before and after the application of SMOTE (Synthetic Minority Over-sampling Technique). Each graph shows the Receiver Operating Characteristic (ROC) curve, which plots the True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity) at various threshold settings. The AUC graph for the Decision Tree classifier shows that, without SMOTE, the ROC curve is relatively steep initially but flattens quickly, indicating moderate performance with a bias towards the majority class. After applying SMOTE, the ROC curve becomes smoother and more balanced, moving closer to the upper left corner of the graph, which suggests an improvement in the model's ability to distinguish between classes. The shaded area around the curve also decreases, indicating increased confidence in the model's predictions after SMOTE application.

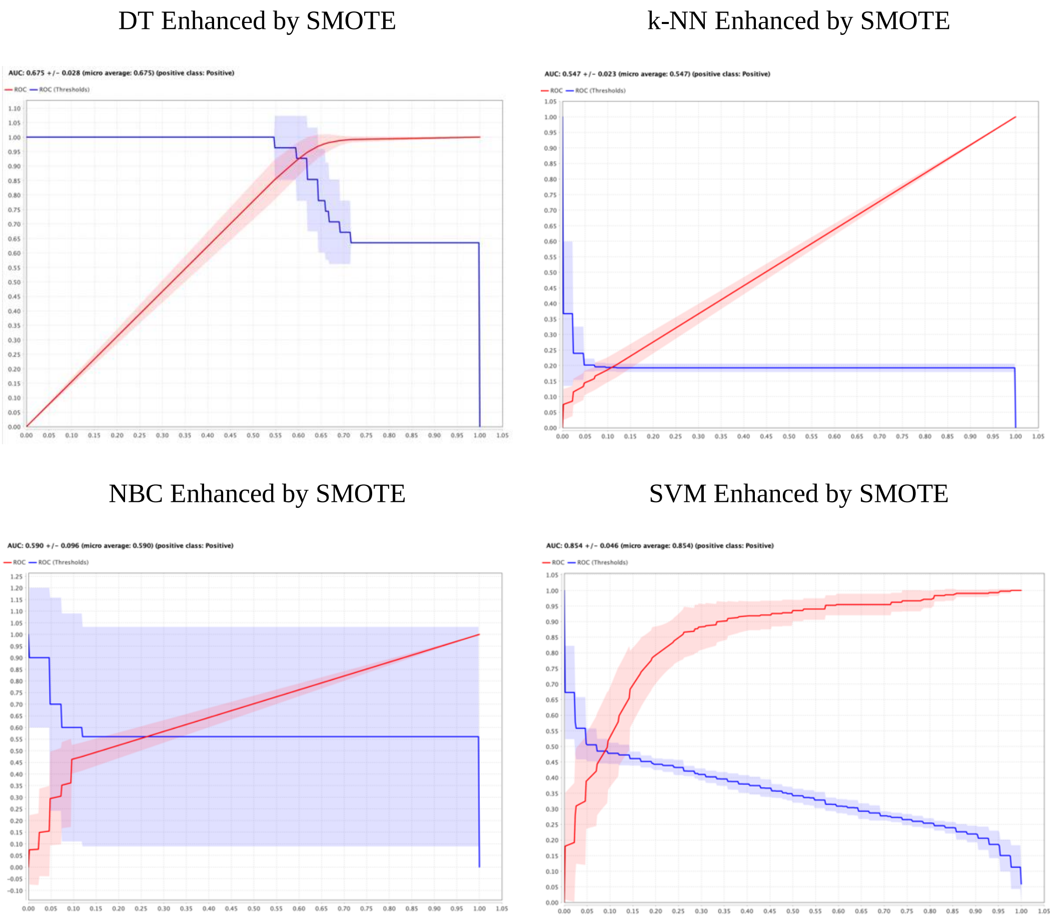

Figure 11. Area Under Curve (AUC) Values of DT, k-NN, NBC, and SVM Enhanced by SMOTE

Figure 11 shows the AUC values of DT, k-NN, NBC, and SVM Enhanced by SMOTE. The k-NN classifier's AUC graph reveals a substantial enhancement post-SMOTE. Initially, the ROC curve is more linear, showing less distinction between the accurate positive and false favorable rates, which is characteristic of a classifier that is less capable of distinguishing between classes. Post-SMOTE, the curve shows a sharper ascent towards the upper left corner, and the AUC value increases, reflecting a significant improvement in the classifier's sensitivity and specificity.

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This change indicates that SMOTE has effectively addressed class imbalance, allowing the k-NN model to perform better. The AUC graph for NBC shows a modest improvement after applying SMOTE. Initially, the ROC curve is somewhat flat, indicating limited discriminative ability. After applying SMOTE, the curve becomes more concave, approaching the ideal diagonal line, although the improvement is less pronounced compared to the k-NN and SVM models. It suggests that while SMOTE helps improve NBC's performance, the gains are modest, possibly due to the model's inherent assumptions, which may not fully benefit from synthetic sampling. The SVM classifier's AUC graph exhibits a clear and substantial improvement post-SMOTE. The initial ROC curve without SMOTE is relatively shallow, indicating poor performance, especially with imbalanced data. However, after applying SMOTE, the ROC curve becomes markedly more convex, almost reaching the upper left corner of the graph. This substantial improvement in the AUC value suggests that SVM, combined with SMOTE, dramatically enhances its capability to classify both the majority and minority classes effectively. The increased AUC indicates that SVM, paired with SMOTE, is highly effective in distinguishing between classes, making it a robust option for handling imbalanced datasets. After applying SMOTE, all four classifiers show improved AUC values, reflecting better model performance and enhanced class discrimination. SMOTE appears particularly effective for k-NN and SVM, significantly boosting their AUC values and ROC curve shapes, indicating a marked improvement in classification accuracy. For DT and NBC, while improvements are noted, they are less pronounced, suggesting that these models benefit from SMOTE but may require additional tuning or alternative approaches for optimal performance in imbalanced scenarios. The analysis confirms that SMOTE is a valuable technique for mitigating class imbalance, leading to more balanced and fair predictive models.

Subsequently, the evaluation results of the VADER model's performance in sentiment extraction, alongside the classification performance of various algorithms, will be compared against toxicity score calculations derived using the Perspective model. This comparative analysis is crucial to determine the effectiveness and accuracy of sentiment analysis tools in capturing nuanced emotional content and potentially harmful language. VADER, being a rule-based sentiment analysis model, offers insights into the emotional tone of the text. In contrast, the Perspective model, which is explicitly designed to assess toxicity levels, provides a more focused measurement of potentially abusive or inappropriate content. Comparing these outcomes allows a deeper understanding of each model's strengths and limitations, particularly distinguishing between sentimentally harmful and genuinely toxic content. This analysis could reveal discrepancies or overlaps between general sentiment extraction and toxicity detection, offering valuable insights into their respective capabilities and informing the development of more refined tools for digital content analysis. Ultimately, this comparative evaluation will enhance the robustness of sentiment and toxicity assessment strategies, ensuring more accurate and reliable outcomes in analyzing user-generated content.

The Perspective model calculates toxicity by leveraging machine learning algorithms that analyze text for specific linguistic patterns and features associated with harmful or abusive language. It operates on a pre-trained model exposed to vast datasets of user comments, which have been manually labeled for varying degrees of toxicity. The model assigns a toxicity score to each piece of text based on the likelihood that the language used is perceived as offensive, disrespectful, or harmful. This scoring process involves evaluating the text for characteristics such as profanity, threats, insults, and hate speech, considering both explicit and implicit forms of toxicity. The Perspective model's effectiveness lies in its ability to capture subtle nuances in language, including context and tone, which may contribute to toxic behavior online. By calculating a toxicity score on a continuous scale, the model provides a nuanced measure of how likely a given text is to be perceived as toxic, allowing for more refined moderation and analysis of online content. This approach enhances the capability of digital platforms to identify and mitigate toxic interactions, promoting healthier online communities.

	Average for dataset	Highest value
Toxicity	0.03972	0.87787
Severe Toxicity	0.00516	0.71339
Identity Attack	0.01134	0.73072
Insult	0.02477	0.80821
Profanity	0.03637	0.85672
Threat	0.01058	0.59966

Figure 12. Average for Dataset and Highest Value of Toxicity Classification (Communalytic)

Figure 12 shows the dataset's average and the highest toxicity classification value using Communalytic. Communalytic's analysis of 23,112 posts, using the Perspective API, provides a detailed assessment of various dimensions of toxicity within the dataset, including metrics for overall toxicity, severe toxicity, identity attack, insult, profanity, and threat. The average toxicity score for the dataset stands at 0.03972, indicating a generally low level of toxicity across the analyzed posts; however, the highest recorded value of 0.87787 suggests that there are individual instances of significantly toxic content. Similarly, severe toxicity has an average score of 0.00516, with a peak value of 0.71339, highlighting a few extreme cases amidst a largely benign dataset. Identity attack and insult scores also

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remain low on average (0.01134 and 0.02477, respectively), though the maximum values reach 0.73072 and 0.80821, reflecting occasional but notable occurrences of harmful language targeting personal attributes. Profanity and threat averages are modest at 0.03637 and 0.01058, respectively, with maximum scores of 0.85672 and 0.59966, indicating rare but severe cases of explicit and aggressive language. These findings suggest that while the overall toxicity levels and offensive language in the dataset are relatively low, the presence of outliers with high toxicity scores warrants attention, underscoring the need for continuous monitoring and moderation to maintain a healthy digital environment.

The toxicity scores derived from the analysis of 23,112 posts using the Perspective API have several important implications for understanding user behavior and managing digital communities. The generally low average scores for toxicity (0.03972), severe toxicity (0.00516), identity attack (0.01134), insult (0.02477), profanity (0.03637), and threat (0.01058) suggest that most interactions within the analyzed dataset are relatively non-toxic and civil. It indicates a positive baseline for community discourse, where harmful or offensive behavior is not prevalent. However, the presence of high maximum values for each category—such as a toxicity score reaching 0.87787, a severe toxicity score of 0.71339, and an identity attack peaking at 0.73072 reveals that there are instances of significantly harmful language that could negatively impact user experience and community health. These high outlier scores imply that while the overall community environment may be conducive to positive interaction, some posts exhibit extreme toxicity, contributing to some users' hostile or unwelcoming atmosphere. Such occurrences may discourage participation, especially among marginalized or vulnerable groups who are more likely to be the targets of toxic behavior. Therefore, these findings underscore the importance of implementing effective content moderation strategies to identify and mitigate instances of high toxicity. Proactive measures, such as automated filtering, human review, and user reporting systems, could be vital in addressing these harmful posts and maintaining a safe and inclusive digital environment. Additionally, understanding the triggers and contexts that lead to toxic interactions can inform the development of targeted interventions and community guidelines to foster more constructive and respectful discourse. These toxicity scores highlight the need for ongoing vigilance and adaptive management to support a healthy, engaging online community.

2.2.4 Content Analysis

Content analysis is essential for comparing toxicity scores with sentiment classification to understand user engagement and behavior in digital environments comprehensively. This approach allows for a nuanced exploration of how different types of user-generated content, ranging from positive sentiment to toxic interactions, contribute to the overall dynamics of online communities. A more holistic view of user interactions is obtained by examining toxicity scores, which measure harmful or offensive language, and sentiment classifications, which assess the emotional tone of the content. Such an analysis provides insights into the complex interplay between constructive and destructive behaviors, revealing patterns that may not be evident when these metrics are considered in isolation. It is argued that integrating these perspectives is crucial to fully capture the multifaceted nature of user engagement, as it considers both the emotional content and the potential for toxicity. Therefore, content analysis serves as a vital tool in identifying the drivers of user behavior and developing strategies to foster positive engagement while mitigating harmful interactions in digital spaces.

The content analysis of this video aligns closely with its audio-visual narrative, which tells the compelling story of a young man named Wisnu embarking on a significant mission to traverse the archipelago of Nusantara. As the chosen descendant of the Maharaja of Nusantara, Wisnu is tasked with performing a sacred tribute to the Garuda, the guardian of the Nusantara. This honor is bestowed only once every century. As the rightful heir of his ancestors, Wisnu has spent years learning the guidance and wisdom passed down by his late father and grandfather, preparing him for this monumental day. His journey is filled with marvels and challenges, symbolizing the trials and tribulations of fulfilling one's destiny. The narrative raises a central question: will Wisnu succeed in his grand quest? This question is a pivotal plot point and engages the audience, inviting them to reflect on the themes of heritage, duty, and perseverance. The story's rich symbolism and dramatic structure provide a layered and meaningful exploration of cultural legacy and personal growth, making it a profound and thought-provoking piece.

Content analysis is essential for understanding user engagement by examining the specific characteristics of a music video that may influence audience behavior and interaction. By systematically analyzing elements such as the video's thematic content, visual aesthetics, narrative structure, and musical composition, insights can be gained into how these features attract and retain viewer attention. It is posited that different aspects of a music video, such as emotional appeal, cultural relevance, and artistic quality, play a significant role in shaping user reactions and engagement levels. The analysis can reveal user engagement patterns, such as increased comments, likes, or shares, which correlate with specific moments or elements within the video, indicating what resonates most with the audience. This detailed understanding of user engagement, grounded in content analysis, enables content creators and digital marketers to tailor their strategies more effectively, enhancing the viewer experience and fostering deeper audience connection. Content analysis provides a comprehensive framework for interpreting user behavior, ensuring digital content strategies align with audience preferences and expectations.

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3. RESULT AND DISCUSSION

The discussion in this research is divided into two main sections: the performance of the toxicity score and sentiment classification models and the exploration of user engagement in digital environments. The first section examines the effectiveness of various models in detecting and classifying toxic content versus positive or neutral sentiment, highlighting their strengths and limitations in accurately capturing the nuances of user interactions. This analysis is crucial for understanding the reliability of these models in differentiating between harmful and constructive user behaviors. The second section delves into user engagement patterns within digital platforms, analyzing how different types of content and sentiment influence user participation, interaction dynamics, and community cohesion. This discussion provides insights into the factors that drive user engagement, including the role of emotional content, perceived safety, and the presence of toxic discourse. By integrating these two aspects, the research offers a comprehensive perspective on how sentiment and toxicity influence user behavior in online spaces, emphasizing the need for robust moderation strategies and positive content reinforcement to foster a healthy digital ecosystem.

3.1 Toxicity Score and Sentiment Classification Model Performance

The calculation of toxicity scores using Communalytic, which analyzed 23,112 posts out of a total of 30,000 using the Perspective API, reveals several key findings regarding the levels of toxic language in the dataset. The average toxicity score across the dataset is relatively low at 0.03972, indicating that most interactions are not overtly harmful or offensive. However, the highest recorded toxicity score of 0.87787 suggests that there are instances of significantly toxic content that could disrupt the digital environment. The scores for severe toxicity, identity attack, insult, profanity, and threat also show low averages (0.00516, 0.01134, 0.02477, 0.03637, and 0.01058, respectively). Yet, their maximum values reach concerning levels, with scores of up to 0.71339 for severe toxicity and 0.85672 for profanity. These figures suggest that while most user interactions are relatively benign, there are notable outliers that reflect the presence of highly offensive or harmful behavior. This disparity between average and maximum values highlights the importance of continued content moderation and community management to mitigate the impact of these extreme instances and maintain a healthy, constructive digital environment.

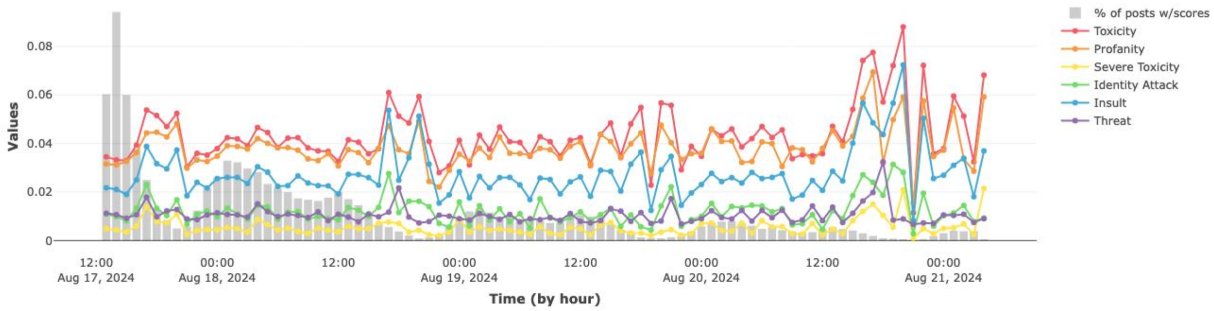

Figure 13. Average Toxicity Score

Figure 13 shows the average toxicity score. The interpretation of the toxicity calculation results, visualized over time, reveals notable patterns in the distribution and intensity of different forms of toxic behavior within the dataset. The time series graph shows fluctuations in toxicity levels, profanity, severe toxicity, identity attack, insult, and threat, with peaks indicating moments of heightened negative sentiment and language use. The consistently higher scores for toxicity and profanity suggest these are the most prevalent forms of negative interaction, with their values frequently spiking throughout the analyzed period, reflecting periods of increased user agitation or conflict. In contrast, the lower but still concerning peaks in severe toxicity, identity attack, insult, and threat highlight less frequent but more severe instances of harmful behavior. The variability in these scores across time suggests that toxic behavior in the digital environment is not constant but instead varies depending on context, content, or external factors, possibly driven by triggering events or discussions. This analysis underscores the importance of dynamic and responsive content moderation strategies that adapt to fluctuating toxicity levels to effectively manage and mitigate harmful interactions in digital communities, ensuring a safer and more inclusive online environment.

The toxicity results should be compared with the sentiment extraction outcomes obtained using the VADER model and the performance of various classification algorithms to gain a more comprehensive understanding of user interactions in digital environments. While toxicity scores provide insights into the presence and intensity of harmful or offensive language, sentiment analysis through VADER offers a broader perspective on the emotional tone of user-generated content, capturing both positive and negative sentiments. Combining these two analyses allows for a more nuanced interpretation of user behavior, distinguishing between merely harmful sentiment and genuinely toxic content. Additionally, evaluating the performance of classification algorithms in this context helps to assess their accuracy and reliability in identifying and categorizing different types of user engagement. By integrating these findings, a more complete picture of digital interactions emerges, highlighting the complexities of online discourse

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and informing the development of more effective moderation strategies to foster constructive communication while curbing toxicity.

Based on the data, the model demonstrating the best performance in sentiment classification is the Support Vector Machine (SVM), which achieves the highest accuracy and balanced performance metrics. The SVM model's accuracy is 68.74%, and its Area Under Curve (AUC) score is 0.686, indicating its superior ability to distinguish between positive and negative sentiment compared to the other models. This higher AUC score reflects a greater discriminative power, suggesting that the SVM model effectively captures the nuances of sentiment within the dataset. Additionally, its precision and recall metrics are well-aligned, further underscoring its balanced capability to identify positive and negative instances accurately. In contrast, the other models, such as Decision Tree (DT), k-nearest Neighbors (k-NN), and Naive Bayes Classifier (NBC), exhibit lower accuracy and AUC scores, indicating comparatively less reliable performance in sentiment classification tasks. The significance of VADER (Valence Aware Dictionary and Sentiment Reasoner) scores lies in their ability to accurately capture the sentiment expressed in text data, particularly in social media and other digital communications. VADER is specifically designed to handle the informal language, slang, emoticons, and abbreviations commonly found in user-generated content, making it a valuable tool for sentiment analysis in online environments. The scores generated by VADER range from -1 (extremely harmful) to +1 (extremely positive), providing a nuanced measurement of sentiment that captures both the polarity (positive or negative) and the intensity of emotions conveyed in the text. These scores are significant because they offer insights into user engagement and behavior, helping to understand how audiences react emotionally to content. High positive or negative scores can indicate strong emotional reactions. In contrast, neutral scores suggest a lack of significant sentiment, providing valuable information for digital marketers, content creators, and community managers aiming to gauge audience sentiment and tailor their strategies accordingly. Moreover, VADER's ability to differentiate between subtle variations in sentiment makes it particularly useful for identifying underlying tones that might not be evident through more straightforward linguistic analysis. By utilizing VADER scores, organizations, and researchers can gain a deeper understanding of public opinion, improve user experience, and foster more effective communication strategies in digital platforms.

Toxicity significantly impacts the outcomes of sentiment analysis by introducing a layer of complexity that affects the interpretation of emotional tone in text data. Toxic language, which includes insults, threats, and identity attacks, often carries a strong negative sentiment that can skew overall sentiment scores towards a more negative classification, even when the broader context might contain mixed or positive emotions. This distortion can lead to misinterpretation of user sentiment, mainly if the sentiment analysis model does not adequately differentiate between general negativity and toxic content. High toxicity may also overshadow other sentiments, causing models to overemphasize the negative aspects and underrepresent the text's more nuanced or positive expressions. Such an outcome can compromise the accuracy and reliability of sentiment analysis, leading to a misunderstanding of user engagement and community sentiment. Therefore, integrating toxicity detection with sentiment analysis is crucial for providing a more balanced and comprehensive understanding of digital interactions, ensuring that the analysis reflects the emotional landscape of the user-generated content.

Linking toxicity and sentiment analysis results to the context of the video in this study provides a deeper understanding of audience engagement and emotional response. The video, which explores themes of cultural heritage and national pride, likely elicits strong emotional reactions, both positive and negative, from viewers. Sentiment analysis results, which measure the overall emotional tone of the comments, reflect the extent to which the content resonates with or alienates the audience. Meanwhile, toxicity analysis identifies harmful language, such as insults or derogatory remarks, that could signal polarizing views or conflicts among viewers. The convergence of high sentiment scores and elevated toxicity levels could indicate that while the video effectively engages viewers emotionally, it also provokes contentious discussions or debates, potentially due to differing interpretations or strong personal feelings about the subject matter. This dynamic interaction between sentiment and toxicity highlights the complex nature of digital engagement, where emotionally charged content can foster both constructive dialogue and toxic behavior.

3.2 Discussion: User Engagement in Digital Environment

User engagement in digital environments plays a crucial role in shaping the dynamics of online communities and influencing content consumption patterns. Active participation, whether through comments, likes, shares, or other forms of interaction, reflects user interest and emotional investment in the presented content. It is argued that higher engagement levels often correlate with a greater sense of community and collective identity among users, fostering positive interactions and heated debates. Analyzing engagement metrics provides valuable insights into user behavior, revealing the content that resonates most strongly and the factors contributing to user satisfaction or dissatisfaction. In this context, understanding the motivations and triggers behind user engagement is essential for creating strategies that encourage constructive discourse while minimizing negative interactions. Ultimately, effective management of user engagement in digital environments can enhance the quality of online discussions, promote a healthier community atmosphere, and drive sustained interaction, benefiting content creators and the broader audience.

User engagement, as reflected in toxicity and sentiment classification results, provides a nuanced perspective on how audiences interact within digital environments. The combination of toxicity scores and sentiment analysis offers a dual-lens through which to assess user interactions' emotional and behavioral dynamics. High sentiment scores generally indicate positive or negative emotional engagement, while elevated toxicity scores suggest the presence of

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harmful or confrontational language, revealing underlying tensions within the community. This interplay between sentiment and toxicity can reveal complex engagement patterns, where users may express strong emotions—whether supportive or critical—about particular content or themes. Such patterns highlight the importance of considering both the emotional tone and the presence of toxicity to understand user behavior and its implications for community dynamics. The findings suggest that fostering a balanced digital environment requires promoting positive sentiment and actively managing and mitigating toxic behavior to ensure constructive engagement and a healthy, inclusive online community.

User engagement and behavior in response to the music video "The Guardian of Nusantara" within the digital environment provide valuable insights into how audiences interact with culturally significant content. The video, which emphasizes national pride and cultural heritage, has elicited a strong response from viewers, as evidenced by high levels of comments, shares, and other forms of digital interaction. This engagement suggests that the video resonates deeply with its audience, triggering emotional connections that motivate users to express their thoughts and feelings publicly. The nature of these interactions, ranging from supportive and positive comments to more critical or reflective ones, indicates the diverse ways the content is received and interpreted. Analyzing this behavior offers a window into the audience's consciousness, revealing how digital content can influence and reflect broader societal values and sentiments.

User engagement in videos is driven by content quality, emotional appeal, relevance, and the ability to resonate with the audience's interests and values. High-quality production elements, such as compelling storytelling, striking visuals, and appealing music, can capture viewers' attention and encourage them to interact with the content. Emotional appeal is a critical driver, as videos that evoke strong emotions—whether joy, nostalgia, excitement, or even outrage—tend to generate higher levels of engagement, prompting viewers to like, share, or comment to express their reactions. Relevance also plays a significant role; videos that align with current trends, social issues, or cultural narratives are more likely to engage viewers who see the content as timely and relatable. Additionally, videos that offer value, such as educational content, entertainment, or inspirational messages, are more likely to attract and retain viewers. Interactivity elements, such as calls to action, interactive features, or viewer participation prompts, can enhance engagement by encouraging viewers to take specific actions.

Cultural elements significantly influence user engagement by shaping how individuals perceive, interpret, and interact with digital content. These elements encompass various factors, including language, values, traditions, symbols, and societal norms, which can affect how content resonates with different audiences. For instance, content that incorporates familiar cultural references uses local languages or dialects, and reflects shared values or beliefs is more likely to engage viewers as it aligns with their cultural context and experiences. Additionally, cultural elements can evoke strong emotional responses, such as pride, nostalgia, or a sense of belonging, which can drive higher levels of engagement through likes, shares, comments, and other forms of interaction. Conversely, content that clashes with or disregards cultural sensibilities may result in lower engagement or adverse reactions. Moreover, cultural factors also determine the types of humor, storytelling techniques, and visual aesthetics that appeal to a specific audience, further influencing their willingness to engage.

User behavior online is influenced by various factors, including psychological, social, cultural, and technological elements. Psychologically, personal motivations, such as the desire for information, entertainment, social connection, or self-expression, play a significant role in determining how users interact with digital content. Social influences, including peer behavior, social norms, and the desire for social validation or recognition, also impact user behavior; for instance, users are more likely to engage with content popular or endorsed by their social networks. Cultural factors, such as language, values, and cultural relevance, affect how users perceive and interact with online content, shaping their preferences and engagement levels. Technological factors, including the design and functionality of platforms, ease of use, accessibility, and interactive features, further shape user behavior by influencing how easily users can access, share, or interact with content. Additionally, external factors such as current events, trending topics, and the overall digital environment, including policies on privacy and content moderation, can influence user behavior by shaping the context in which online interactions occur.

4. CONCLUSION

The study concludes that user engagement within digital environments, particularly in the context of creative content such as music videos, is significantly influenced by sentiment and toxicity levels in user interactions. Utilizing the Digital Content Reviews and Analysis Framework, the study identifies that while 95.8% of interactions exhibit a positive or neutral sentiment, a notable presence of toxic comments (4.2%) reflects broader societal tensions and can create a feedback loop that perpetuates negativity. The toxicity results from analyzing 23,112 posts using the Perspective API reveal that the average toxicity score is relatively low at 0.03972. However, there are instances of significantly toxic content, with the highest recorded toxicity score reaching 0.87787. Severe toxicity, identity attack, insult, profanity, and threat scores also show low averages (0.00516, 0.01134, 0.02477, 0.03637, and 0.01058, respectively), yet their maximum values are notably higher, with severe toxicity peaking at 0.71339 and profanity at 0.85672. These findings suggest that extreme cases require attention and continuous monitoring while the toxicity levels are low. The sentiment classification results, conducted using the VADER model and various classification algorithms, indicate that the Support Vector Machine (SVM) model achieved the best performance in accurately categorizing user sentiment. The SVM model demonstrated the highest accuracy at 68.74% and an Area Under Curve (AUC) score of 0.686, indicating its superior ability to distinguish between positive and negative sentiment compared to other models like Decision Tree (DT), k-nearest Neighbors (k-NN), and Naive Bayes Classifier (NBC). This robust performance underscores the effectiveness of SVM in handling sentiment classification tasks, particularly in complex digital environments. In the discussion of user engagement within digital environments, the study explores how active participation through comments, likes, and shares is a critical indicator of user interest and emotional investment in the content. The findings suggest that high levels of engagement often correlate with a sense of community and shared identity among users, fostering both positive interactions and, at times, intense debates. The analysis reveals that while positive engagement enhances community cohesion and content reception, toxic interactions can undermine these benefits, creating a hostile environment that deters constructive dialogue. Therefore, fostering positive user engagement is essential for content creators and platform managers to maintain a vibrant digital community and mitigate toxicity's negative impact. This dynamic highlights the importance of the Digital Content Reviews and Analysis Framework in systematically evaluating user interactions and content, emphasizing the need for compelling content moderation and strategies to promote a balanced and respectful online discourse. Furthermore, the research underscores the necessity for more sophisticated tools and methodologies, such as sentiment analysis and toxicity detection, to analyze user engagement accurately, ensuring that digital spaces remain conducive to meaningful and productive discussions. Overall, the study provides valuable insights into the complex interplay between user sentiment, engagement, and the impact of toxic discourse in shaping digital communities.

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