



# Implementation of Perspective, Vader, and TextBlob in Toxicity and Sentiment Analysis of Food and Tourism

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**Abstract**—This research investigates the sentiment and toxicity of viewer responses to digital content on food and tourism using the Digital Content Reviews and Analysis Framework. Employing advanced text processing and sentiment analysis models such as Perspective, TextBlob, and Vader, the study analyzed 4,166 comments. The findings reveal a predominantly positive viewer sentiment, with VADER identifying 18.98% negative, 21.33% neutral, and 59.69% positive sentiments, while TextBlob identified 14.42% negative, 33.86% neutral, and 51.72% positive sentiments. The toxicity analysis highlighted various levels, with an average toxicity score of 0.15783 and notable scores for severe toxicity, identity attack, insult, profanity, and threat. The research underscores the importance of comprehensive sentiment analysis in understanding viewer engagement, providing valuable insights for content creators and marketers in the tourism industry. The study concludes with recommendations for further exploration and refinement of sentiment analysis methodologies to enhance the understanding and management of digital content interactions.

**Keywords:** Food and Tourism; Perspective; Vader; TextBlob; Sentiment; Toxicity

## 1. INTRODUCTION

Food and tourism are inseparable, particularly in destinations renowned for their culinary attractions or unique food and beverage offerings. This symbiotic interaction drives the local economy and enhances cultural exchange and visitor satisfaction [1]–[3]. Integrating local gastronomy into tourism experiences fosters an authentic engagement with the destination, creating memorable and sensory-rich experiences [4]–[6]. Consequently, developing culinary tourism strategies is paramount in maximizing a region's appeal and promoting sustainable tourism practices. Ultimately, the fusion of food and tourism catalyzes cultural preservation and economic growth, underscoring its pivotal role in the tourism industry.

Tourism flourishes through the presence of attractions, accommodations, accessibility, and amenities in a destination, aligning with and fulfilling the needs and preferences of travelers. Attractions are the primary draw, captivating visitors with unique cultural, natural, or entertainment experiences [7], [8]. Accommodations and amenities ensure comfort and convenience, enhancing the overall travel experience [9], [10]. Accessibility, encompassing transportation and infrastructure, is crucial in enabling easy and efficient movement within the destination [11]–[13]. Therefore, strategically integrating these elements is essential for fostering a thriving tourism industry, demonstrating the importance of a holistic approach to destination management.

Moreover, the economic, socio-cultural, and environmental benefits derived from the growth of the tourism sector significantly contribute to sustainability. Economic advantages include job creation, increased revenue, and improved infrastructure, collectively boosting local economies [14]. Socio-cultural benefits encompass cultural preservation, enhanced cross-cultural understanding, and community empowerment [15]–[17]. Environmental benefits arise from sustainable tourism practices that promote conservation and the responsible use of natural resources [18]–[20]. Therefore, the multifaceted advantages of tourism development play a crucial role in fostering sustainability, illustrating its integral value in balancing economic growth, cultural integrity, and environmental stewardship.

This study uses toxicity and sentiment analysis approaches to analyze viewer sentiment toward food and tourism content, leveraging the Perspective, Vader, and TextBlob models. The perspective model provides insights into the toxicity levels of comments, enabling the identification of potentially harmful content. Vader and TextBlob model offers nuanced sentiment analysis, capturing viewer feedback's emotional tone and polarity. Integrating these models enhances the depth and accuracy of sentiment analysis, making it a robust methodology for understanding audience reactions. Consequently, this research contributes valuable insights into viewer perceptions, facilitating creating more engaging and positively received content.

This research's multifaceted theoretical and practical contributions provide valuable insights and applications within the academic and industry spheres. Theoretically, the study advances the understanding of sentiment analysis methodologies by integrating Perspective, Vader, and TextBlob models, thus enriching the literature on computational linguistics and its application in tourism studies. Practically, the findings offer actionable insights for content creators and marketers, enabling the development of more targeted and engaging

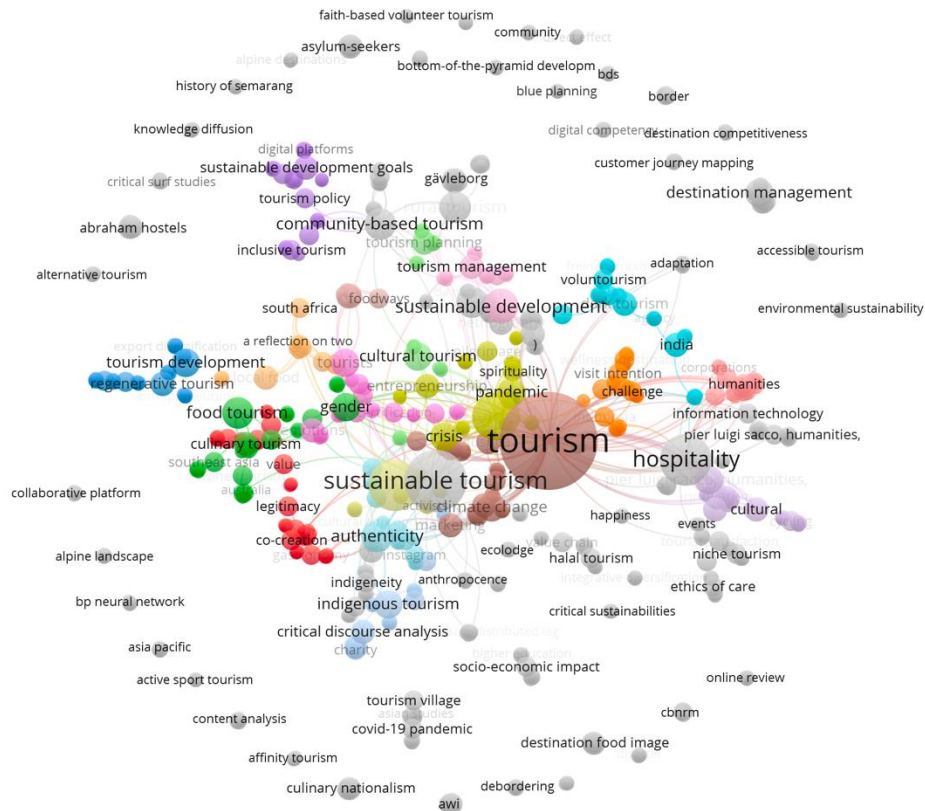
food and tourism content. This research underscores its significance in fostering academic advancements and practical innovations by bridging theoretical frameworks with real-world applications.

Similar research in sentiment analysis on food and tourism content often employs models such as Perspective, Vader, and TextBlob to evaluate audience reactions. These studies typically focus on the effectiveness of these models in capturing nuanced emotional responses and identifying toxic language. However, limitations persist, such as the models' varying accuracy in different linguistic contexts and the challenges in processing complex, context-dependent sentiments. Despite these constraints, integrating multiple models enhances the robustness of analysis. Addressing these limitations through ongoing refinement and contextual adaptation will significantly improve the reliability and applicability of sentiment analysis in this domain.

## 2. RESEARCH METHODOLOGY

### 2.1 Tourism and Remote Sensing Research

To understand the context of food and tourism, this research identifies gaps in previous studies related to the issue of food and tourism. These gaps often include a lack of comprehensive analysis on integrating culinary experiences with tourism strategies and insufficient exploration of the socio-cultural impacts of gastronomic tourism. Addressing these gaps is crucial for understanding how food influences tourist behaviors and destination attractiveness. Consequently, this research aims to fill these voids by providing a more detailed examination of the intersection between food and tourism, ultimately contributing to more effective and inclusive tourism development strategies.



**Figure 1.** Gap Analysis using Vosviewer

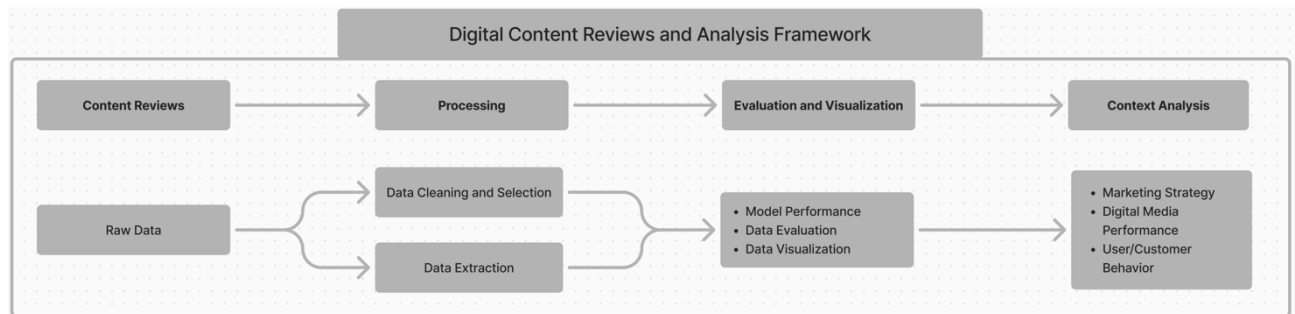
Figure 1 shows the network visualization of current research related to food and tourism studies. Current research on food and tourism can be examined from the perspectives of sustainability and tourism development. Recent studies emphasize integrating sustainable practices within culinary tourism to mitigate environmental impacts and promote local economies [21]–[23]. Additionally, research highlights the role of food tourism in fostering sustainable development by enhancing cultural heritage and community engagement [24]–[26]. The interplay between these factors underscores the need for a holistic tourism planning approach. Consequently, this dual focus on sustainability and development advances theoretical understanding and provides practical frameworks for sustainable tourism initiatives.

Based on the identification of gaps in the study of food and tourism, it is evident that sustainability issues and destination development play a crucial role in enhancing tourist satisfaction and benefiting local communities. However, examining viewer perceptions or responses to digital content about food and tourism is also essential.

Therefore, this research proposes an analysis of the toxicity and sentiment of viewer content related to food and tourism to comprehensively and thoroughly depict tourist preferences. This approach addresses existing gaps and provides valuable insights for improving digital engagement strategies in the tourism sector.

### 2.2 Digital Content Reviews and Analysis Framework

This study adopts the Digital Content Reviews and Analysis Framework for processing review data concerning digital content on food and tourism, aiming to analyze marketing strategies, digital tool performance, and tourist behavior. This framework enables a systematic evaluation of how digital content influences consumer decisions and destination appeal. By examining various digital platforms, the study provides insights into the effectiveness of current marketing tactics and the technological engagement of tourists. Consequently, this approach offers a comprehensive understanding of the digital landscape, facilitating the development of more effective and targeted tourism marketing strategies.



**Figure 2.** Digital Content Reviews and Analysis Framework

Figure 2 shows the Digital Content Reviews and Analysis Framework. The Digital Content Reviews and Analysis Framework comprises several stages: content reviews, processing, evaluation and visualization, and context analysis. Initially, content reviews involve systematically gathering and categorizing digital content related to food and tourism. The processing stage entails cleaning and structuring the data for further analysis. Evaluation and visualization, then data analysis using various metrics and tools, presenting the findings comprehensibly and impactfully. Lastly, context analysis interprets these findings within the broader scope of tourism trends and behaviors. This structured approach ensures a comprehensive and insightful examination of digital content, enhancing strategic decision-making in tourism marketing.

Considering the framework's relevance to the research context, this study holds significant importance. Integrating a systematic approach for analyzing digital content and viewer sentiment aligns well with the objectives of understanding food and tourism dynamics. The research aims to provide comprehensive insights into audience engagement and preferences using advanced keyword analysis and sentiment detection methodologies. Consequently, the findings will contribute to academic knowledge and offer practical implications for enhancing digital content strategies in the tourism sector. Thus, the execution of this research is crucial for advancing theoretical and practical domains.

#### 2.2.1 Content Reviews

In the content review stage, examining the digital content and accompanying review data (text data) to ensure relevance to the data processing objectives is crucial. This involves meticulously selecting and categorizing content that aligns with the research goals, focusing on aspects that significantly impact the analysis. Proper examination of review data aids in identifying key themes and sentiments, enhancing the precision of subsequent analysis stages. Therefore, a thorough and systematic approach to content reviews is essential for achieving meaningful and relevant outcomes in the overall data processing framework.

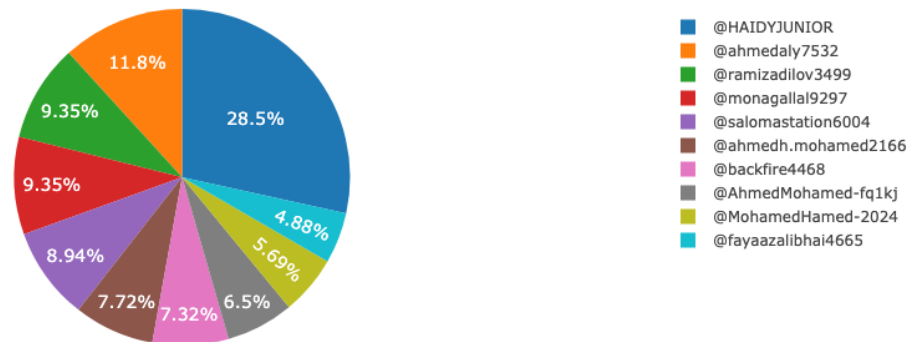


**Figure 3.** Video and Post-Per-Day Statistic (Communalytic)

Figure 3 shows the post-per-day statistic of the content. Based on post-per-day statistical data, the number of comments per date exhibits fluctuation, indicating viewer engagement as reflected in the following data: 2022-

04-10 (1345 comments), 2022-04-11 (614 comments), 2022-04-12 (270 comments), 2022-04-13 (182 comments), 2022-04-14 (111 comments), 2022-04-15 (81 comments), 2022-04-16 (68 comments), 2022-04-17 (67 comments), 2022-04-18 (56 comments), and 2022-04-19 (45 comments). This variation highlights peaks and troughs in viewer interaction, with notable spikes on specific dates. Such patterns suggest periods of heightened interest, possibly due to specific content features or external factors. Understanding these fluctuations can inform strategies to optimize viewer engagement and tailor content more effectively to audience preferences.

Subsequently, an analysis of the top ten posters reveals the channel owners connected with the content creators and their contributions to the comment and reply statistics. This analysis identifies the most active contributors, highlighting their engagement levels and influence within the digital community. Such data provides insight into the dynamics of user interactions, illustrating the significant role these top posters play in shaping discussions and driving viewer engagement. Understanding their impact is crucial for leveraging influential users to enhance content reach and interaction. This strategic approach can optimize content dissemination and community-building efforts.



**Figure 4.** Top Ten Poster

Figure 4 shows the top ten posters of the content. The top ten poster data reveals the percentage contributions of various channels to the comments on this content as follows: @HAIDYJUNIOR (28.5%), @ahmedaly7532 (11.8%), @ramizadilov3499 (9.35%), @monagalla9297 (9.35%), @salomastation6004 (8.94%), @ahmedh.mohamed2166 (7.72%), @backfire4468 (7.32%), @AhmedMohamed-fq1kj (6.5%), @MohamedHamed-2024 (5.69%), and @fayaazalibhai4665 (4.88%). This distribution indicates the varying levels of engagement among these contributors, with @HAIDYJUNIOR demonstrating the highest activity. Such data provides valuable insights into user interaction dynamics, illustrating top contributors' influence on the overall engagement metrics. Understanding these patterns is essential for optimizing community management and enhancing content strategy.



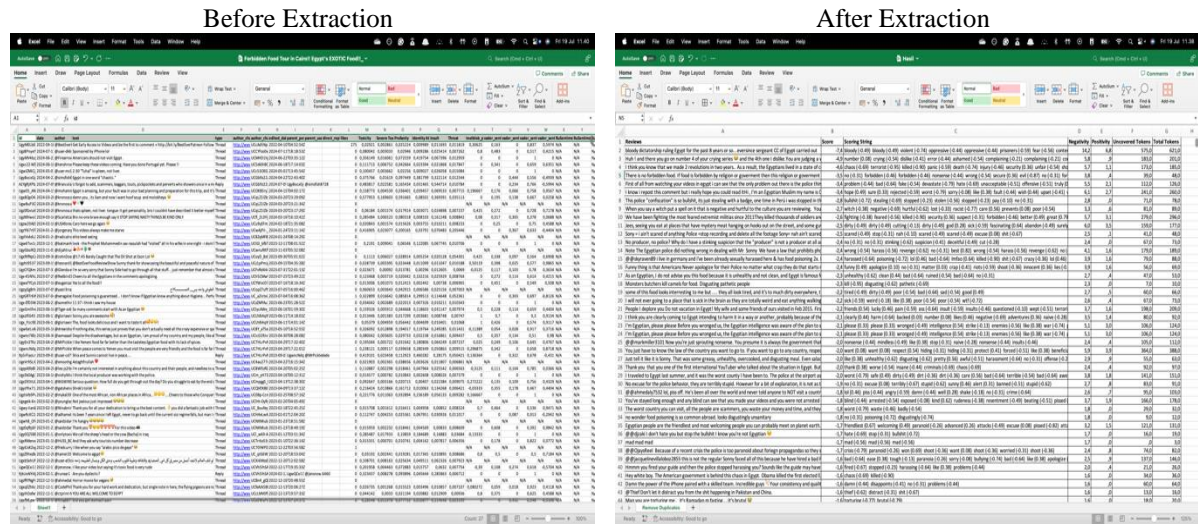
**Figure 5.** Emoji Cloud Based on Dataset

Figure 5 shows the emoji cloud based on the dataset. Viewers frequently use specific emojis when reviewing the content. The most used emoji is 😂, appearing 46 times, indicating a humorous or entertaining perception of the content. Other commonly used emojis include 🇮🇩 (15 times), ❤️ (14 times), 🇮🇩 (11 times), and 🇮🇩 (11 times), reflecting positive reactions and appreciation. Emojis such as 🍔 (10 times) and 🇪🇬 (10 times) also indicate a connection to food enjoyment and possibly cultural identity. The frequent use of these emojis highlights the viewers' emotional engagement and diverse reactions. Consequently, understanding these patterns is crucial for tailoring content to meet audience preferences and enhance viewer satisfaction.

Subsequently, the most frequently appearing words in viewer comments can be utilized to identify sentiment through keyword analysis. This method involves extracting standard terms and phrases that indicate



Figure 7 shows the data selection and cleaning process on Rapidminer. After cleaning 4,167 data entries using operators such as tokenize, transform cases, filter tokens, stopwords, and stem, the process continues with text data extraction for classification. This involves categorizing the comments into positive, neutral, and negative classes using the Vader model. The classification process leverages Vader's ability to gauge sentiment intensity and polarity within the text accurately. This step is crucial for understanding the overall sentiment distribution, providing valuable insights into viewer reactions. Consequently, this systematic approach enhances the reliability and depth of the sentiment analysis, contributing significantly to the research objectives.



**Figure 8.** Data Extraction Result

Figure 8 shows the data extraction result. Based on the extraction results, it is evident that there are 4,041 data reviews, with 122 classified in the hostile class and 3,918 in the positive class. This distribution indicates a predominantly positive sentiment among the viewer comments, suggesting a favorable content reception. The relatively small number of negative reviews highlights the content's effectiveness in engaging and satisfying the audience. Such insights are crucial for content creators and marketers, enabling them to tailor their strategies to maintain and enhance positive viewer engagement. Consequently, the sentiment analysis provides a comprehensive understanding of audience perception, informing future content development.

Subsequently, the extracted and classified data, labeled as negative and positive, will be evaluated based on the performance of the best algorithm and visualized in user-friendly graphical formats. This evaluation involves comparing various algorithms to identify the most accurately classified sentiment. The visualization step translates complex data into intuitive charts and graphs, facilitating a clear understanding of user sentiment distribution. This approach ensures the information is accurate and accessible, enhancing its utility for stakeholders in strategic decision-making. Thus, rigorous evaluation and effective visualization underscores the study's contribution to comprehensible data presentation.

### 2.2.3 Evaluation and Visualization

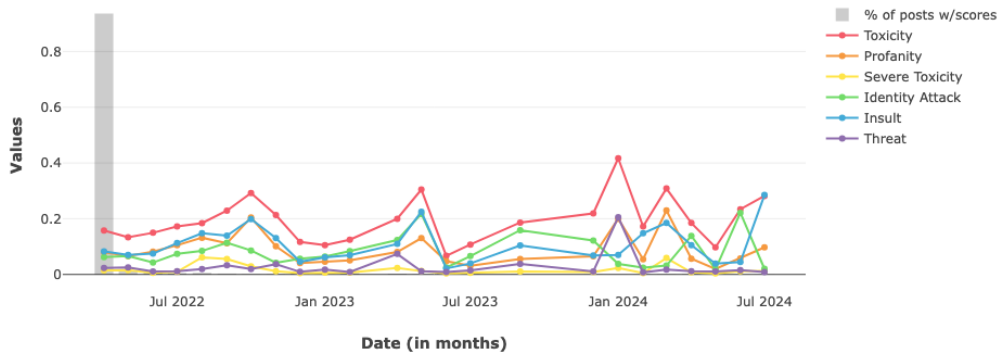
The classification results will be evaluated and supervised in the data evaluation and visualization stage before proceeding to algorithm-based model testing using k-NN, SVM, DT, and NBC. This phase involves assessing the accuracy and reliability of the initial classification to ensure data integrity. Supervising the classification results is crucial for identifying any inconsistencies or errors that might affect the subsequent model testing. By implementing k-NN, SVM, DT, and NBC algorithms, the study aims to determine the most effective model for sentiment analysis. Consequently, this thorough evaluation process enhances the robustness and credibility of the research findings.

Based on the data selection results, it is determined that 2,830 text data entries are suitable for the modeling process, considering the string scores derived from the Vader model-based extraction. This selection ensures that only high-quality and relevant data are utilized for subsequent analysis, enhancing the accuracy of the sentiment classification. The string scores provide a quantitative measure of sentiment intensity, effectively categorizing text data. Consequently, the refined dataset serves as a robust foundation for developing predictive models, thereby improving the reliability and validity of the research outcomes.

The SMOTE operator is employed during the classification process with the k-NN, SVM, DT, and NBC algorithms to balance the data. This technique addresses the issue of class imbalance by generating synthetic samples for the minority class, thereby improving the model's performance. Using SMOTE ensures that the classification algorithms can more accurately identify patterns and relationships within the data. Consequently, this approach enhances the robustness and predictive accuracy of the models, leading to more reliable and valid research findings.



Based on the toxicity calculation results of the digital content with ID nuSHSnnz4cg, it is evident that the toxicity levels are highly variable and can be classified as Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat. This classification enables a detailed understanding of the different types and intensities of toxic behavior in the comments. The variability in toxicity levels highlights the diverse nature of viewer interactions and the necessity for targeted moderation strategies. Consequently, these insights can inform more effective content management and community guidelines to foster a healthier online environment.

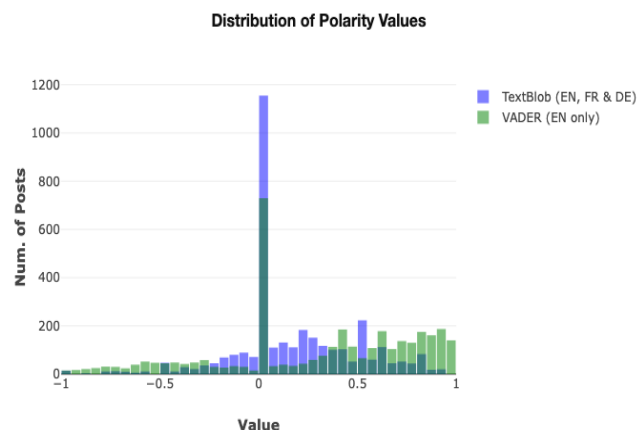


**Figure 10.** Toxicity Scores Based on Perspective

Figure 10 shows the toxicity scores per month. The identification and analysis of toxicity values from 3,819 posts out of 4,166 reveal the following metrics: Toxicity ranges from 0.15783 to 0.92100, Severe Toxicity from 0.01479 to 0.56528, Identity Attack from 0.06327 to 0.64879, Insult from 0.08347 to 0.78565, Profanity from 0.07992 to 0.90862, and Threat from 0.02291 to 0.65430. These values indicate a wide range of toxic behaviors present in the comments, with varying degrees of severity. The highest levels of toxicity and profanity underscore significant issues within the viewer interactions. Consequently, these findings necessitate implementing robust moderation strategies to mitigate harmful content and promote a safer online community.

The identification and analysis of toxicity values from 3,819 posts out of 4,166 provide a comprehensive view of the nature and severity of toxic behaviors in viewer comments. The toxicity scores, ranging from 0.15783 to 0.92100, indicate a significant presence of harmful interactions, with the upper range reflecting highly toxic comments. Severe Toxicity, although lower in frequency (0.01479 to 0.56528), still represents a critical area of concern due to its potential impact on community well-being. Identity Attack values (0.06327 to 0.64879) highlight discrimination or personal attacks, necessitating focused interventions. Insults (0.08347 to 0.78565) and Profanity (0.07992 to 0.90862) are prevalent, showcasing the need for compelling content moderation tools to maintain a respectful discourse. The presence of Threats (0.02291 to 0.65430), although less frequent, underscores the importance of monitoring for safety risks. These findings emphasize the need for comprehensive strategies to address and mitigate toxic behavior, fostering a healthier and more inclusive online environment.

Subsequently, the classification results of 3,532 out of 4,166 posts using the Vader and TextBlob models into negative, neutral, and positive classes reveal distinct sentiment distributions. For Vader (English/EN), out of 3,488 posts, 662 (18.98%) exhibited negative sentiment, 744 (21.33%) were neutral, and 2,082 (59.69%) showed positive sentiment. Similarly, for TextBlob (English/EN), out of 3,488 posts, 503 (14.42%) were classified as unfavorable, 1,181 (33.86%) as neutral, and 1,804 (51.72%) as positive. These findings illustrate variations in sentiment detection between the two models, highlighting differences in sensitivity and classification thresholds. Consequently, understanding these differences is crucial for selecting appropriate models for sentiment analysis in specific research contexts.

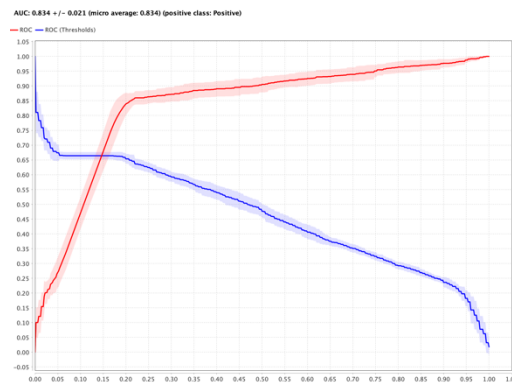


**Figure 11.** Sentiment Classification based on Vader and TextBlob

Figure 11 shows the distribution of polarity values based on Vader and TextBlob performance. VADER and TextBlob agree on categorizing 2,355 (68.68%) out of 3,429 English language posts. This level of agreement is considered moderate, as indicated by Cohen's kappa statistic of 0.471. The moderate agreement level suggests that while there is a significant overlap in sentiment classification between the two models, notable discrepancies still exist. These differences may arise from each model's distinct algorithms and approaches to analyzing text sentiment. Consequently, this agreement level underscores the importance of model selection and the potential need for combining multiple sentiment analysis tools to achieve more robust results.

Expressly, both libraries agree on the classification of sentiments in the following manner: 287 (12.19%) posts with negative sentiments (polarity scores  $\leq -0.05$ ), 551 (23.40%) posts with neutral sentiments (polarity scores between  $-0.05$  and  $0.05$ ), and 1,517 (64.42%) posts with positive sentiments (polarity scores  $\geq 0.05$ ). This consensus highlights the alignment between VADER and TextBlob in identifying the overall sentiment of most posts. The significant proportion of favorable sentiment agreement suggests a general favorability towards the content. In contrast, the moderate agreement on neutral and negative sentiments points to areas where sentiment detection can be nuanced. Consequently, these findings emphasize the reliability of both models for sentiment analysis in digital content evaluation.

There were 140 posts where VADER assigned positive polarity scores while TextBlob assigned negative scores, and 147 posts where VADER assigned negative polarity scores while TextBlob assigned positive scores. These discrepancies highlight the differences in sentiment interpretation between the two models, which can be attributed to their distinct analytical frameworks. Such divergences underscore the complexity of accurately categorizing sentiment in text data, mainly when models employ varying algorithms and linguistic rules. Consequently, these findings suggest the potential benefit of combining multiple sentiment analysis tools to achieve a more comprehensive understanding of text sentiment.



**Figure 12.** Area Under Curve (AUC) of SVM using SMOTE

Figure 12 shows the SVM performance evaluation result. The performance evaluation of the SVM algorithm using SMOTE reveals an accuracy of  $72.21\% \pm 2.73\%$  (micro average: 72.21%). The confusion matrix indicates 817 true negatives, 151 false positives, 682 false negatives, and 1,348 true positives. The optimistic AUC is  $0.882 \pm 0.020$  (micro average: 0.882), the standard AUC is  $0.834 \pm 0.021$  (micro average: 0.834), and the pessimistic AUC is  $0.787 \pm 0.023$  (micro average: 0.787). Precision is  $66.44\% \pm 2.28\%$  (micro average: 66.40%), while recall is  $89.93\% \pm 2.32\%$  (micro average: 89.93%). The F-measure is calculated at  $76.41\% \pm 2.18\%$  (micro average: 76.40%). These results demonstrate the algorithm's robust performance, particularly in recall, but also highlight areas for improvement in precision to enhance overall predictive accuracy.

The performance analysis of the SVM algorithm using SMOTE indicates a commendable accuracy of  $72.21\% \pm 2.73\%$ , with a notable recall rate of  $89.93\% \pm 2.32\%$ , suggesting the model's strong capability to identify positive instances. The confusion matrix reveals many false negatives (682) and false positives (151), contributing to a precision of  $66.44\% \pm 2.28\%$ . The AUC values—optimistic at  $0.882 \pm 0.020$ , standard at  $0.834 \pm 0.021$ , and pessimistic at  $0.787 \pm 0.023$ —demonstrate the model's reliable discriminatory power. However, the disparity between precision and recall suggests a need for refining the model to reduce false classifications and improve precision. Overall, the SVM with SMOTE exhibits robust performance, especially in the recall, but requires optimization to enhance its precision and balanced accuracy.

This research demonstrates that the processing of digital content reviews on food and tourism reveals a predominantly positive viewer response, as evidenced by the results of text pre-processing and processing using toxicity and sentiment analysis approaches. The application of Perspective, TextBlob, and Vader models in the analysis effectively highlights the overall favorable sentiment among the audience. These findings underscore the effectiveness of employing multiple analytical models to understand viewer feedback comprehensively. Consequently, the study provides valuable insights into audience perceptions, affirming the positive reception of food and tourism content.

Future research recommendations focus on expanding the scope and depth of sentiment analysis in digital content related to food and tourism. This includes incorporating more advanced machine learning algorithms to



improve the accuracy and granularity of sentiment detection. Extending the analysis to include a broader range of social media platforms can provide a more comprehensive understanding of audience perceptions across different digital environments. Further investigation into the impact of cultural and regional differences on sentiment expression also enhances the relevance and applicability of findings. Ultimately, these advancements will contribute to a more nuanced and practical approach to analyzing viewer responses in the food and tourism sector.

## 4. CONCLUSION

The conclusion of this research highlights the significant insights gained from analyzing digital content reviews on food and tourism using the Digital Content Reviews and Analysis Framework. This framework has effectively demonstrated a predominantly positive viewer response by applying advanced text processing and sentiment analysis models, including Perspective, TextBlob, and Vader. The toxicity score analysis of 3,819 posts revealed various toxicity levels, with an average toxicity score of 0.15783, severe toxicity at 0.01479, identity attack at 0.06327, insult at 0.08347, profanity at 0.07992, and threat at 0.02291. The sentiment classification results, based on 3,532 posts, indicated that VADER identified 18.98% negative, 21.33% neutral, and 59.69% positive sentiments, while TextBlob identified 14.42% negative, 33.86% neutral, and 51.72% positive sentiments. This comprehensive approach, structured through the stages of content reviews, data processing, evaluation and visualization, and context analysis, has validated the utility of these models in understanding audience sentiment. The findings provide valuable information for content creators and marketers in the tourism industry. The research emphasizes the importance of leveraging diverse analytical tools within a structured framework to capture the nuances of viewer feedback, thereby enhancing strategic decision-making and content development. This study underscores the potential for further exploration and refinement in sentiment analysis methodologies to continue improving the understanding of digital content engagement.

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