SENTIMENT ANALYSIS FOR TOURISM DESTINATION REVIEWS USING CROSS-INDUSTRY STANDARD PROCESS FOR DATA-MINING

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ABSTRACT

This study investigates sentiment analysis methodologies in the tourism domain, addressing the challenge of extracting meaningful insights from user-generated content, specifically TripAdvisor reviews of S.E.A Aquarium and Gardens by the Bay in Singapore. The research applies the CRISP-DM framework to develop and evaluate sentiment classification models, including Naive Bayes Classifier (NBC), k-nearest Neighbors (k-NN), Decision Trees (DT), and Support Vector Machines (SVM). A key problem addressed is the class imbalance in the data, which is mitigated using SMOTE, significantly enhancing model accuracy from 0.500 to 0.992. Performance differences across models are assessed through comprehensive t-tests, revealing significant results with p-values ranging from 0.000 to 0.182. The models are evaluated using metrics such as accuracy, precision, recall, AUC, and F-measure, with SVM demonstrating the best overall performance. Additionally, a word frequency analysis highlights recurring themes in tourist feedback. The study's findings contribute to a deeper understanding of sentiment analysis in tourism, offering valuable insights for improving tourist experiences and guiding destination management strategies.
Keywords: *Sentiment Analysis, Tourism Reviews, TripAdvisor Data, VADER*

1. INTRODUCTION

Sentiment analysis is an integral component of artificial intelligence performance, encompassing the Natural Language Processing process in discerning text and categorizing it based on sentiment [1]. In consumer satisfaction analysis, tourist review data assumes significance in appraising business performance; hence, sentiment analysis is imperative [2]–[5]. By employing advanced algorithms, this computational method efficiently evaluates the polarity of textual data, facilitating informed decision-making processes and enhancing business strategies to bolster consumer satisfaction and loyalty.

Visitor review data in tourist destinations is valuable for enhancing tourism services and supporting facilities [6]–[10]. Sentiment analysis emerges as a pertinent and practical approach to addressing issues within the tourism service sector [11]–[14]. By harnessing sentiment analysis techniques, stakeholders in the tourism industry gain comprehensive insights into visitor sentiments and tailoring services and amenities to meet evolving consumer expectations and preferences [15]–[17]. Consequently, integrating sentiment analysis into tourism management strategies holds immense potential for optimizing visitor experiences and bolstering destination competitiveness in the global tourism landscape.

The method proposed as a solution to address the research problem is CRISP-DM (Cross-Industry Standard Process for Data Mining). This well-established methodology provides a systematic framework for guiding the entire data mining process, from business objectives and data understanding to evaluation and deployment [18]. Using CRISP-DM, this research effectively navigates the complexities of analyzing tourist review data, ensuring methodological rigor and facilitating the generation of meaningful insights [19]–[22]. Consequently, adopting CRISP-DM holds promise in enhancing the efficiency and efficacy of sentiment analysis in the tourism sector, thereby contributing to informed decision-making and strategic planning in the industry.

The urgency of this research lies in the necessity for practical models to process vast amounts of tourist review data into actionable recommendations for the tourism industry. Consequently, this study addresses the pressing need for efficient data analysis methodologies tailored to the tourism sector's unique requirements. By developing effective models for analyzing and synthesizing tourist feedback, businesses glean valuable insights to enhance service quality, improve customer satisfaction, and ultimately elevate the competitiveness of tourism enterprises in today's dynamic market landscape.

The research aims to analyze and extract tourist review texts using the Valence Aware Dictionary for Sentiment Reasoning (VADER) [23]–[28]. By leveraging this computational tool, the study explores the nuanced sentiments expressed within tourist feedback, elucidating the underlying emotional valence of the textual content [29]–[35]. Through systematic evaluation and classification, VADER facilitates a comprehensive understanding of the sentiment dynamics inherent in tourist reviews, thereby furnishing invaluable insights for businesses seeking to optimize customer satisfaction strategies and refine service offerings in the tourism sector.

This research's practical and theoretical contributions are paramount in advancing the understanding and application of sentiment analysis techniques in tourism. By developing robust methodologies for analyzing vast volumes of tourist review data, this study offers practical insights for enhancing tourism service quality [36]–[40]. It contributes to the theoretical frameworks underpinning sentiment analysis in the context of consumer behavior and satisfaction [41]–[44]. Through meticulous examination and synthesis of tourist sentiments, this research furnishes actionable recommendations for businesses to optimize service offerings, fostering sustainable growth and competitiveness in the tourism industry.

The limitations of this research are primarily attributed to the utilization of the CRISP-DM methodology, the specific context of the S.E.A Aquarium and Garden by the Bay destination in Singapore, and the reliance on review data sourced exclusively from TripAdvisor. While CRISP-DM offers a structured approach to data mining, its applicability may be constrained by the unique complexities inherent in the tourism domain, potentially necessitating supplementary methodologies to address nuanced sentiment dynamics. Furthermore, focusing solely on the S.E.A Aquarium and Garden by the Bay destination may limit the generalizability of findings to broader tourism contexts. Additionally, reliance on TripAdvisor reviews may introduce biases inherent in online user-generated content platforms, potentially influencing the robustness and representativeness of the dataset. Hence, careful consideration of these limitations is imperative for interpreting the findings and extrapolating insights within the specified scope of this research.

The significance of sentiment analysis in tourism lies in its ability to uncover tourists' perceptions, preferences, and pain points, which are often hidden in unstructured review data. Tourism is a competitive and experience-driven industry, and understanding the sentiments expressed by visitors is crucial for improving services, enhancing customer satisfaction, and maintaining a destination's competitive edge. Traditional methods of collecting feedback, such as surveys, often fall short in capturing the depth and variety of opinions freely expressed in user-generated content. Sentiment analysis offers a scalable solution to this problem, enabling stakeholders to process vast amounts of review data and derive actionable insights to inform better decision-making.

This study adopts the CRISP-DM framework to systematically address the challenges of sentiment analysis in tourism. By applying this methodology, the research progresses through clear stages, from understanding business needs to evaluating the models used for sentiment classification. Techniques like SMOTE (Synthetic Minority Over-sampling Technique) are employed to mitigate issues of data imbalance, a common problem in sentiment analysis where positive reviews often outnumber negative ones. This approach enhances the reliability of the classification

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models used Naive Bayes, k-NN, Decision Trees, and SVM ensuring that even minority class sentiments are accurately identified and analyzed. This structured methodology not only ensures the robustness of the research findings but also provides a replicable framework for future studies in the tourism sector.

2. RELATED WORK

2.1 Sentiment Analysis in Tourism

Tourist sentiment analysis constitutes a pivotal component of a business strategy aimed at devising innovative programs to enhance tourist satisfaction during destination visits [5]. By systematically analyzing the sentiments expressed in tourist feedback, businesses gain valuable insights into visitor perceptions, preferences, and experiences, thereby informing the development of tailored initiatives to address identified needs and enhance overall satisfaction levels [45]. Consequently, integrating sentiment analysis into strategic decision-making processes enables tourism enterprises to optimize resource allocation, refine service offerings, and cultivate enduring relationships with visitors, ultimately fostering sustainable growth and competitiveness in the dynamic tourism industry landscape.

Based on the findings of the literature review, it is evident that tourist behavior is intricately linked to sentiments expressed in the form of reviews. Tourist behavior encompasses a spectrum of actions and decisions tourists undertake during travel experiences, influenced by various factors such as personal preferences, cultural backgrounds, and external stimuli [46]. Within this context, sentiments conveyed through tourist reviews serve as a valuable indicator of visitor perceptions, satisfaction levels, and preferences, offering insights into the underlying motivations and experiences driving tourist behavior [47]. Consequently, recognizing and understanding the interplay between tourist behavior and sentiment analysis is crucial for tourism stakeholders seeking to optimize service delivery, enhance visitor experiences, and maintain competitive advantage in the dynamic tourism marketplace.

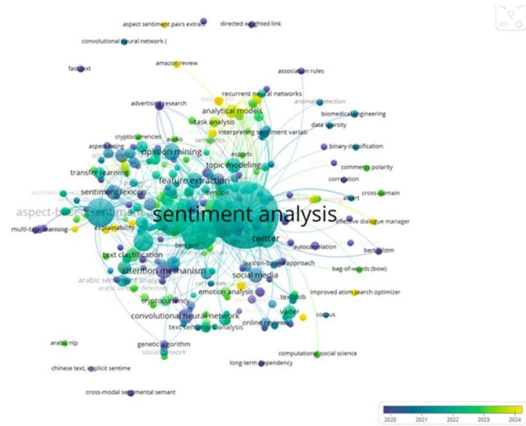

Figure 1: The Overlay Visualization of Previous Research Entitled Sentiment Analysis

Figure 1 presents the overlay visualization of previous research entitled Sentiment Analysis. The study of sentiment analysis has gained widespread popularity and warrants specific examination within the tourism business sector. As tourism continues to flourish globally, businesses within this sector increasingly recognize the importance of understanding and responding to the sentiments expressed by tourists [48], [49]. Sentiment analysis provides a systematic approach to deciphering the emotions, opinions, and experiences conveyed through tourist feedback, thereby offering valuable insights for enhancing service quality, tailoring marketing strategies, and fostering customer satisfaction [50]. Consequently, the burgeoning interest in sentiment analysis underscores its relevance and significance as a strategic tool for driving innovation and competitiveness in the dynamic landscape of tourism businesses.

The contextual examination of sentiment analysis is imperative across various sectors, including tourism. This research explicitly addresses tourist behavior, motivation, and satisfaction within the tourism sector. This study aims to elucidate the complex interplay between tourist sentiments and behaviors, motivations, and overall satisfaction levels by delving into the intricacies of sentiment analysis within the tourism context. Such contextual analysis enhances our understanding of tourist dynamics. It offers actionable insights for businesses to tailor strategies and services to meet tourists' evolving needs and preferences, ultimately fostering sustainable growth and competitiveness in the tourism industry.

2.2 Tourist Behaviour, Satisfaction, and Motivation

Tourist behavior manifests in traveler actions and decisions that reflect preferences for facilities and services at tourist destinations, significantly influencing tourist satisfaction levels. This comprehensive depiction of tourist actions encompasses a spectrum of activities, including accommodation choices, dining preferences, and engagement with recreational activities, all of which contribute to shaping the overall tourist experience [51]. Consequently, understanding and effectively responding to the nuanced dynamics of tourist behavior is paramount for tourism businesses aiming to optimize service delivery, enhance visitor satisfaction, and maintain a competitive advantage in the global tourism marketplace.

Tourist satisfaction is intricately linked to tourist motivation, whereby positive visit outcomes often correlate with a heightened likelihood of return visits. This interplay between satisfaction and motivation underscores the pivotal role that positive experiences play in shaping tourists' future behaviors and decisions [52]. When tourists perceive visitation experiences positively, it reinforces the motivation to revisit the destination, driven by the desire to recreate or build upon the enjoyable aspects of the previous visit [53]. Consequently, prioritizing efforts to enhance tourist satisfaction becomes instrumental in fostering repeat visitation and cultivating enduring relationships with tourists, thereby contributing to destination sustainability and competitiveness in the tourism industry.

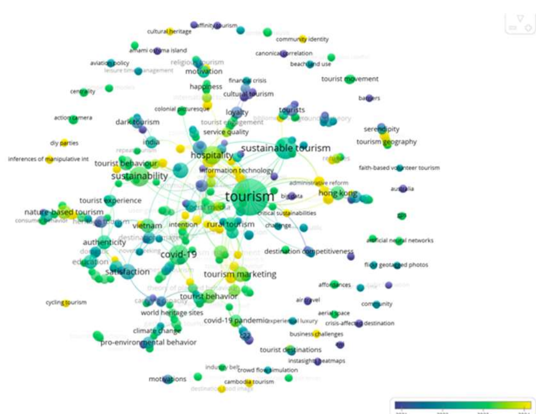

Figure 2: The Density Visualization of Previous Research Entitled Tourist Behavior

Figure 2 presents the density visualization of previous research entitled Tourist Behavior. Tourist motivation is intricately intertwined with pull and push factors, contingent upon satisfaction levels following a visit to a tourist destination [54]. Pull factors encompass the allure and attractions that draw tourists to a particular destination, such as natural landscapes, cultural heritage, or recreational opportunities [55]. At the same time, push factors represent internal or external forces that impel individuals to travel, such as seeking adventure or escaping routine [56]. However, the efficacy of both pull and push factors in influencing tourist behavior ultimately hinges on the degree of satisfaction experienced during the visit. Positive visitation experiences reinforce pull factors by fulfilling tourists' expectations and desires while mitigating push factors by providing gratification and fulfillment [57]. Thus, understanding the complex interplay between tourist motivation and satisfaction is essential for destination management, enabling stakeholders to leverage pull factors effectively and address push factors to optimize tourist experiences and destination competitiveness.

Based on previous research on tourist behavior, satisfaction, and motivation, it is evident that text data in the form of tourist reviews is harnessed to provide recommendations for enhancing facilities and services at tourist destinations. Businesses and destination management organizations gain valuable insights into visitor preferences, experiences, and satisfaction levels by systematically analyzing the sentiments expressed within these reviews [58]. This informed understanding of tourist sentiments enables stakeholders to identify areas for improvement, tailor offerings to meet visitor expectations, and elevate the overall quality of the tourist experience [59]. Consequently, leveraging text data for recommendation generation represents a strategic approach to optimizing destination management strategies and enhancing competitiveness in the tourism industry.

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

The CRISP-DM approach is highly relevant for evaluating review data to discern tourist satisfaction, motivation, and behavior. This methodological framework offers a structured and systematic process for data mining, encompassing various stages such as business understanding, data understanding, modeling, evaluation, and deployment [60]. By adhering to the CRISP-DM methodology, this research navigates the complexities of analyzing tourist review data, ensuring methodological rigor and facilitating extracting meaningful insights. Consequently, leveraging the CRISP-DM approach enables stakeholders to comprehensively understand tourist sentiments and behaviors, make informed decisions, and implementing targeted strategies to enhance visitor experiences and destination competitiveness.

TripAdvisor and YouTube are valuable data sources for identifying viewer or tourist responses through destination-related review columns. These platforms offer vast repositories of user-generated content, including textual reviews, ratings, and video uploads, providing rich insights into visitor experiences, preferences, and sentiments [61]. Leveraging these sources enables destination managers and businesses to comprehensively understand visitor perceptions and feedback, facilitating informed decision-making processes and targeted interventions to enhance destination offerings and visitor satisfaction [62]. Consequently, harnessing data from TripAdvisor and YouTube represents a strategic approach to gathering real-time insights and staying attuned to evolving visitor needs and preferences in the dynamic tourism landscape.

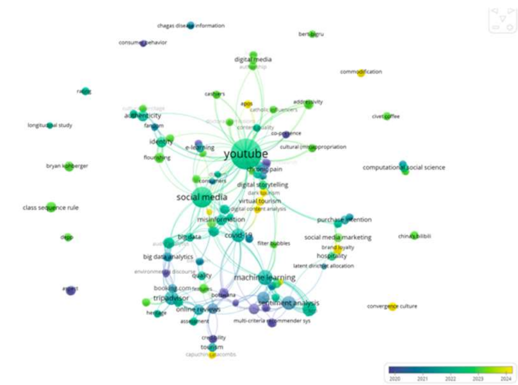

Figure 3: The Density Visualization of Previous Research using Data Mining based on YouTube and TripAdvisor Reviews

Figure 3 presents the density visualization of previous data-mining research using YouTube and Tripadvisor reviews as data sources. TripAdvisor and YouTube reviews serve as valuable data sources for evaluating services at tourist destinations. Several studies have highlighted the diverse responses from tourists depending on the context of the tourism business [63], [64]. These platforms provide a wealth of user-generated content, offering insights into visitor experiences, satisfaction levels, and preferences [65]. By analyzing reviews from TripAdvisor and YouTube, destination managers and businesses gain valuable insights into areas of strength and areas for improvement, enabling them to tailor offerings to meet the needs and expectations of tourists better [66], [67]. Consequently, leveraging data from these platforms represents a strategic approach to enhancing service quality and visitor satisfaction in the tourism industry.

Thus, the CRISP-DM framework effectively utilizes text data from TripAdvisor and YouTube reviews to be processed into valuable information to enhance the quality of tourism services. Leveraging this structured methodology enables destination managers and businesses to systematically analyze tourists' sentiments, preferences, and feedback, facilitating informed decision-making processes and targeted interventions to improve service offerings. By harnessing data from these platforms within the CRISP-DM framework, stakeholders gain actionable insights to address areas of concern, optimize resource allocation, and elevate the overall visitor experience, fostering destination competitiveness and sustainability in the tourism industry landscape.

2.4 K-NN, NBC, DT, and SVM Performance Evaluation

This study employs k-NN, NBC, DT, and SVM models for sentiment classification based on negative and positive classes, with performance evaluation focusing on accuracy, precision, recall, F-measure, and Area Under Curve (AUC) metrics. The research uses these machine-learning algorithms to effectively categorize sentiment polarity in textual data, distinguishing between users' negative and positive sentiments research utilizing k-NN, NBC, DT, and SVM; it is evident that these machine-learning algorithms are utilized within text data classification. K-nearest neighbor (k-NN) [68], Naïve Bayes Classifier (NBC) [69], Decision Trees (DT) [70], and Support Vector Machines (SVM) [71] are widely recognized for efficacy in handling textual data classification tasks, owing to the ability to discern patterns and relationships within complex datasets effectively [72]. The visualization outcomes provide valuable insights into the performance and interpretability of k-NN, NBC, DT, and SVM models in text classification scenarios, highlighting the utility of extracting meaningful insights from textual data and informing decision-making processes in various domains, including sentiment analysis, information retrieval, and natural language processing.

Based on the relevance of k-NN, NBC, DT, and SVM models within the CRISP-DM framework, the research context within the tourism sector becomes coherent. The CRISP-DM framework provides a structured approach to data mining, encompassing various stages such as business

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understanding, data understanding, data preparation, modeling, evaluation, and deployment. By integrating k-NN, NBC, DT, and SVM models into this framework, this research systematically analyzes tourist sentiment data, extracts meaningful insights, and informs decision-making processes to enhance service quality and visitor satisfaction. Consequently, aligning k-NN, NBC, DT, and SVM models with the CRISP-DM framework facilitates a cohesive and systematic approach to addressing challenges and opportunities within the tourism industry, ultimately fostering destination competitiveness and sustainability.

The primary goal of this study was to develop and evaluate sentiment analysis models tailored to tourism reviews by utilizing the CRISP-DM framework and addressing class imbalance issues with SMOTE. In terms of outcomes, the study successfully implemented Naive Bayes, k-NN, Decision Trees, and Support Vector Machines, with SVM emerging as the top-performing model. The integration of SMOTE notably enhanced model accuracy, particularly in handling imbalanced datasets, which aligned with the initial objectives of providing a robust solution for sentiment classification.

However, there are areas for critique. While the study's methodology and outcomes reflect significant improvements in model performance, the reliance on a single data source—TripAdvisor—limits the generalizability of the findings. Incorporating multiple review platforms could have provided a more comprehensive understanding of tourist sentiments. Additionally, while SMOTE helped address class imbalance, more advanced methods like cost-sensitive learning or deep learning architectures could have further improved performance, particularly in distinguishing minority sentiment classes.

In comparison to current state-of-the-art solutions, this study's use of traditional machine learning models like Naive Bayes and Decision Trees lags behind the more sophisticated methods frequently used in sentiment analysis today, such as deep learning-based approaches. Techniques like BERT (Bidirectional Encoder Representations from Transformers) and hybrid models that combine word embeddings with neural networks have demonstrated superior performance in handling natural language data. For instance, studies have shown that transformer-based models can outperform traditional algorithms in both sentiment classification and contextual understanding, as seen in recent literature [29], [73].

Moreover, the use of VADER for sentiment analysis, while effective for smaller datasets, may not provide the nuanced understanding that more complex algorithms offer, especially in large-scale, multi-lingual, or highly subjective reviews. Current research often integrates ensemble learning or transfer learning models, which provide better generalization and adaptability across domains. In conclusion, while this study made valuable contributions by improving accuracy through SMOTE and employing structured methodologies, it could benefit from integrating more advanced machine learning techniques seen in state-of-the-art literature. Incorporating these methods would likely lead to better performance, especially in processing complex and imbalanced sentiment data.

3. METHODOLOGY

3.1 Research Design

This research adopts a quantitative, data-driven design using the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework to systematically analyze user-generated review data from TripAdvisor. The decision to employ CRISP-DM is grounded in its proven effectiveness across various industries, including marketing and healthcare, for transforming raw data into actionable insights. Prior studies in other regions, such as Japan's tourism sector, highlight the utility of sentiment analysis in understanding tourist behaviors and improving visitor experiences [2]. Similarly, in industries like e-commerce, sentiment analysis has been successfully applied to improve customer satisfaction by evaluating product reviews [50]. In the healthcare domain, similar sentiment analysis techniques used to mine feedback from patients, demonstrating its cross-disciplinary application in different forms of consumer review data [73].

In tourism, where reviews are often unstructured and voluminous, sentiment analysis provides a solution to efficiently capture the overall sentiment and key feedback trends. However, a persistent challenge is the imbalance of review data—positive reviews often outnumber negative ones, making it difficult for traditional models to accurately classify sentiment. This study integrates SMOTE (Synthetic Minority Over-sampling Technique) to address this issue, similar methodologies to analyze consumer sentiments in cultural heritage tourism. By addressing these common challenges through advanced machine learning models like SVM (Support Vector Machine) and Naive Bayes, the study not only contributes to tourism research but also

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demonstrates the generalizability of these methods across different sectors [74].

The research design in this study adheres to the CRISP-DM framework, providing a structured and systematic approach to data mining and analysis. The CRISP-DM framework encompasses distinct phases, including business understanding, data understanding, data preparation, modeling, evaluation, and deployment, each crucial in guiding the research process. By following this established framework, this research effectively navigates the complexities of sentiment analysis within the tourism sector, ensuring methodological rigor and facilitating extracting meaningful insights from tourist review data. Consequently, aligning the research design with the CRISP-DM framework enables stakeholders to make informed decisions and implement targeted strategies to enhance service quality and visitor satisfaction in the tourism industry.

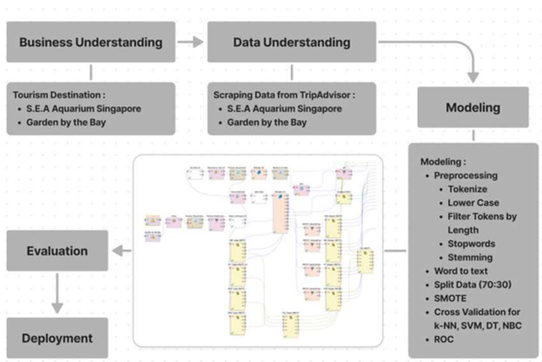

Figure 5: The research workflow

Figure 5 presents the research workflow. Based on the research workflow, the business understanding phase within the CRISP-DM framework indicates that the textual data context comprises reviews limited to the S.E.A Aquarium destinations in Singapore. This initial phase involves gaining insight into the objectives, requirements, and constraints of the business problem at hand, which, in this case, involves understanding tourist sentiments and preferences within specific tourist destinations. By delineating the scope and context of the data, this research effectively formulates research questions, hypotheses, and analytical strategies tailored to the unique characteristics of the tourism sector, ultimately facilitating the development of targeted interventions to enhance service quality and visitor satisfaction within the specified destinations.

Subsequently, data collection is conducted using WebHarvy, which retrieves information based on account names, ratings, review titles and content, dates of visit, and destination management replies. This data collection process is vital for acquiring information from online platforms such as TripAdvisor and YouTube, where user-generated content provides valuable insights into tourist sentiments and experiences. By systematically gathering relevant data points, this research builds comprehensive datasets for analysis to extract meaningful insights and inform decision-making processes to enhance service quality and visitor satisfaction within the tourism sector.

3.2 Datasets

The dataset collected originates from TripAdvisor and was selected based on the relevance of its context to specific tourist destinations visited by travelers. TripAdvisor is a prominent online platform where tourists share experiences and opinions about various attractions and accommodations, offering valuable insights into visitor sentiments, preferences, and satisfaction levels. By sourcing data from TripAdvisor, this research accesses a wealth of user-generated content tailored to the tourism domain and analyzes and interprets tourist feedback effectively. Consequently, leveraging TripAdvisor data facilitates a comprehensive understanding of tourist experiences and perceptions, empowering stakeholders to make informed decisions and implement targeted strategies to enhance service quality and visitor satisfaction within the tourism industry.

Table 1: Extract Sentiment of TripAdvisor Reviews

Reviews	Sentiment	String Score
Try and allocate a couple of hours for this attraction when you are in the Sentosa district or get here regardless. The complex has an amazing set of display tanks containing everything from clown fish to whale sharks. The main tank being the highlight which contains grey nurse sharks, rays, turtles, shell fish all part of a huge coral reef ecosystem. Fish from all over the world, including fresh and salt water environments from the Amazon to the Great Barrier Reef. If you have never gone snorkelling or scuba diving, or never intend to, this is probably one of the best exihibitions to visit in the world to see what is under the surface of the waves and how marine ecosystems operate. There are plenty of educational dioramas and interactive touch screens to keep you informed of what is on display. Of course, there is also a shop and	Positive	Total Score : 4,5 Score String : attraction (0.51) amazing (0.72) highlight (0.36) grey (0.05) huge (0.33) fresh (0.33) amazon (0.18) great (0.79) barrier (-0.13) diving (0.08) best (0.82) save (0.56) avoid (-0.31) recommended (0.21)

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refreshments section. To save a bit of time, pre book and try for mid week to avoid major crowds. Highly recommended.		
Sentosa island only 10mins away from Marina Bay, S$10 by taxi. We did the SEA aquarium, cost S$39 per person. You have to walk through a pathetic maritime museum first, then into the aquarium. Over crowded with screaming kids, adults let them run riot. There are ropes to keep people back from the walls of the glass fish tanks, yet everyone walks over them. You cant see the fish through the arrogant people who push up to the glass. This should be policed by staff so everyone can see the fish..	Negative	Total Score : 4,5 Score String : pathetic (-0.69) screaming (-0.41) riot (-0.67) arrogant (-0.56)

Table 1. presents the review data after pre-processing and extracting through the VADER process. The review data obtained from TripAdvisor undergoes a cleansing process and is extracted using VADER to obtain scores and score strings before being classified into positive or negative categories. This preprocessing step is crucial for ensuring the quality and reliability of the data used for sentiment analysis. By applying VADER, which stands for Valence Aware Dictionary for Sentiment Reasoning, this research accurately assesses the sentiment polarity of each review, assigning a numerical score and corresponding score string based on the emotional valence conveyed in the text. Subsequently, classifying the reviews into positive or negative categories enables this research to discern overall sentiment trends and patterns, facilitating more profound insights into visitor perceptions and satisfaction levels within the tourism sector.

4. EXPERIMENT AND RESULT

By employing advanced data mining techniques, such as the CRISP-DM framework and SMOTE, sentiment classification models will be able to overcome the challenges of imbalanced datasets in tourism reviews, leading to significantly improved accuracy in identifying both positive and negative sentiments. This improvement will provide actionable insights for tourism stakeholders, enabling them to enhance customer satisfaction and tailor their services more effectively.

4.1 Experiment Results

In the first experiment, the processed data comprises textual reviews of the S.E.A Aquarium in Singapore, totaling 1908 data entries. These reviews are extracted using the VADER (Valence Aware Dictionary and sEntiment Reasoner) tool, with a dataset split of 70% for testing and 30% for training, and employing the Synthetic Minority Over-sampling Technique (SMOTE). This experimental setup allows for evaluating sentiment analysis models trained on imbalanced datasets, ensuring robustness and accuracy in classification tasks. By systematically processing and analyzing the S.E.A Aquarium review data, this research gains valuable insights into visitor sentiments and satisfaction levels, informing decision-making processes to enhance service quality and visitor experiences within the tourism sector.

Table 2: Model Performance of Sentiment Classification Using SMOTE

Model	NBC	k-NN	DT	SVM
Accuracy	99.18%	50.04%	96.80%	96.05%
Precision	98.39%	50.02%	99.10%	92.74%
Recall	100.00%	100.00%	94.45%	100.00%
AUC	0.549	0.531	0.967	1.000
F-Measure	99.19%	66.68%	96.71%	96.22%

Table 2. shows the result of the model performance of sentiment classification using SMOTE. The comparative results of the models indicate significant variations in performance metrics: NBC achieved the highest accuracy at 99.18%, followed by Decision Trees (DT) at 96.80%, Support Vector Machines (SVM) at 96.05%, and k-nearest Neighbors (k-NN) with the lowest accuracy of 50.04%. Precision scores also reflected these differences, with NBC achieving the highest precision of 98.39%, while k-NN exhibited the lowest precision at 50.02%. However, it is noteworthy that k-NN demonstrated the highest recall rate of 100.00%, suggesting its effectiveness in correctly identifying positive instances. SVM surpassed other models with the highest Area Under Curve (AUC) score of 1.000, indicating its superior performance in classification tasks. While NBC emerged as the top-performing model in terms of accuracy and precision, choosing the most suitable model depends on specific requirements and trade-offs between performance metrics.

Table 3: Model Performance of Sentiment Classification Without Using SMOTE

Model	NBC	k-NN	DT	SVM
Accuracy	94.24%	95.81%	95.28%	95.88%
Precision	7.69%	33.33%	25.00%	unknown
Recall	3.33%	1.67%	7.33%	0.00%
AUC	0.499	0.661	0.500	0.819
F-Measure	4.94%	3.45%	11.27%	unknown

Table 3. shows the model performance of sentiment classification without using SMOTE. The comparative analysis of the models reveals notable

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discrepancies in performance metrics: Naive Bayes Classifier (NBC) attained an accuracy of 94.24%, k-nearest Neighbors (k-NN) achieved 95.81%, Decision Trees (DT) yielded 95.28%, and Support Vector Machines (SVM) obtained 95.88%. Precision scores varied significantly across models, with NBC exhibiting the lowest precision at 7.69%, followed by k-NN at 33.33%, DT at 25.00%, and SVM with an unknown value. Additionally, recall rates were notably low for all models, with NBC at 3.33%, k-NN at 1.67%, DT at 7.33%, and SVM at 0.00%. SVM demonstrated the highest Area Under Curve (AUC) score of 0.819, indicating its superior performance distinguishing between positive and negative instances. While NBC had the lowest precision and recall rates, choosing the most appropriate model depends on the specific objectives and requirements of the sentiment analysis task.

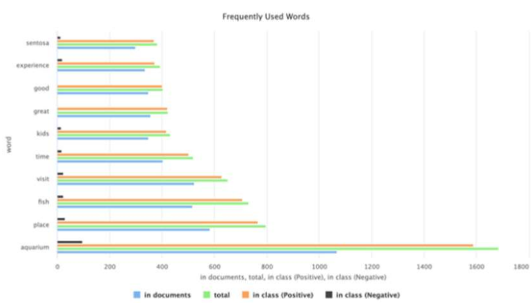

Figure 6: Frequently Used Words in S.E.A Aquarium Datasets

Figure 6 shows the frequently used words. Based on the results of identifying frequently used words, it is evident that specific terms dominate the discourse surrounding the topic. The word "aquarium" emerges as the most frequently mentioned term, appearing 1067 times, followed by "place" with 582 occurrences. Other prominent terms include "fish" (516 occurrences), "visit" (523 occurrences), and "time" (404 occurrences), reflecting common themes related to the aquarium experience. Additionally, terms such as "kids," "great," "good," and "experience" denote positive sentiments associated with the visit, while "Sentosa" indicates the specific location context. These findings provide valuable insights into the critical aspects of visitor experiences and perceptions, facilitating targeted interventions and improvements to enhance visitor satisfaction and overall tourism experiences within the aquarium setting.

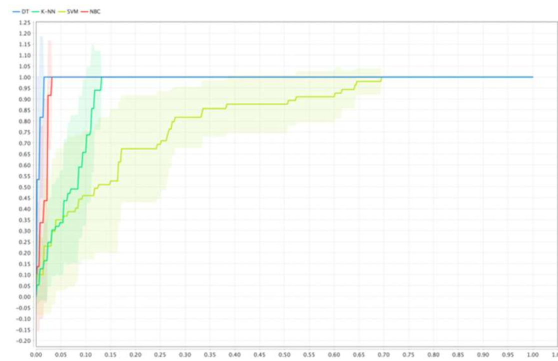

Figure 7: ROC Comparison based on S.E.A Aquarium Datasets

Figure 7. shows the ROC Comparison of NBC, k-NN, DT, and SVM. A higher Area Under Curve (AUC) is a reliable indicator of classifier performance, with values closer to 1 suggesting superior discrimination ability. This metric is particularly advantageous in scenarios characterized by imbalanced class distributions, where Receiver Operating Characteristic (ROC) curves provide valuable insights into classifier effectiveness across different discrimination thresholds. By visually depicting the trade-off between actual positive and false favorable rates, ROC curves enable direct comparisons between classifiers, aiding in selecting the most suitable model for a given task. Consequently, leveraging AUC and ROC curves enhances decision-making processes in classifier evaluation, ultimately contributing to optimizing predictive modeling outcomes in various domains.

The t-test analysis results indicate a notable trend: the probabilities for random values aligning with the same outcome steadily decrease, reaching a noteworthy probability of 0.000 across the board. This pattern underscores a substantial likelihood of significant differences between the mean values being compared. Additionally, values smaller than the established alpha level of 0.050 support this inference, suggesting statistically significant variations. The performance values, respective means, and standard deviations further elucidate the observed differences. Notably, performance metrics 0, 1, 2, and 3 demonstrate mean estimates of 0.500, 0.992, 0.968, and 0.961, respectively, with associated standard deviations of 0.001, 0.005, 0.010, and 0.014. These findings underscore the statistical robustness of the observed disparities, as confirmed by the t-test analysis.

The second experiment involves the performance evaluation of models based on 1243 review data from the Garden by the Bay destination, partitioned into 30% training data and 70% testing

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data. This experimental setup aims to assess the generalizability and effectiveness of the sentiment analysis models specifically tailored to the characteristics of the Garden by the Bay destination. By systematically evaluating model performance on a separate dataset, this research validates the robustness and reliability of the models in real-world scenarios, providing insights into the suitability for practical applications within the tourism domain. Consequently, this experiment contributes to refining and optimizing sentiment analysis methodologies, ultimately enhancing decision-making processes to improve visitor experiences and satisfaction levels within tourist destinations like the Garden by the Bay.

Table 4: Model Performance of Sentiment Classification Using SMOTE

Model	NBC	k-NN	DT	SVM
Accuracy	99.59%	50.06%	97.69%	97.76%
Precision	99.19%	50.03%	97.99%	95.75%
Recall	100.00%	100.00%	97.40%	100.00%
AUC	0.500	0.470	0.981	1.000
F-Measure	99.59%	66.69%	97.69%	97.82%

Table 2. shows the result of the model performance of sentiment classification using SMOTE. The evaluation results of models utilizing the Synthetic Minority Over-sampling Technique (SMOTE) highlight distinct performance disparities across classifiers. Naive Bayes Classifier (NBC) exhibits the highest accuracy at 99.59%, closely followed by Decision Trees (DT) at 97.69% and Support Vector Machines (SVM) at 97.76%. While k-Nearest Neighbors (k-NN) demonstrates the lowest accuracy of 50.06%, the Precision metric shows NBC with the highest precision of 99.19%, followed by DT at 97.99% and SVM at 95.75%. Furthermore, NBC achieves a perfect recall rate of 100.00%, indicating its ability to identify all relevant instances accurately. At the same time, SVM attains the highest Area Under Curve (AUC) score of 1.000, underscoring its superior discriminatory power. Despite these variations, the F-Measure highlights NBC as the top-performing model with 99.59%, emphasizing its balanced precision and recall rates.

Table 5: Model Performance of Sentiment Classification Without Using SMOTE

Model	NBC	k-NN	DT	SVM
Accuracy	96.44%	97.24%	97.24%	97.24%
Precision	0.00%	unknown	50.00%	unknown
Recall	0.00%	0.00%	5.00%	0.00%
AUC	0.500	0.605	0.500	0.738
F-Measure	unknown	unknown	7.69%	unknown

Table 3. shows the model performance of sentiment classification without using SMOTE. The evaluation outcomes of models without employing the Synthetic Minority Over-sampling Technique (SMOTE) reveal notable variations in performance across classifiers. While the Naive Bayes Classifier (NBC) achieves an accuracy of 96.44%, k-nearest Neighbors (k-NN), Decision Trees (DT), and Support Vector Machines (SVM) exhibit identical accuracy scores of 97.24%. However, precision metrics for NBC and SVM are undefined, while k-NN demonstrates a precision of 50.00% and DT exhibits 0.00%. Additionally, NBC and k-NN models yield a recall and F-Measure of 0.00%, emphasizing the limitations in correctly identifying relevant instances. Notably, k-NN stands out with the highest Area Under Curve (AUC) score of 0.605, suggesting moderate discriminatory ability compared to other models. Despite these variances, the absence of precision, recall, and F-Measure values for NBC underscores the need to interpret its performance in sentiment analysis tasks carefully. In summary, the evaluation outcomes underscore the necessity of comprehensively considering diverse performance metrics to assess classifier efficacy in SMOTE's absence.

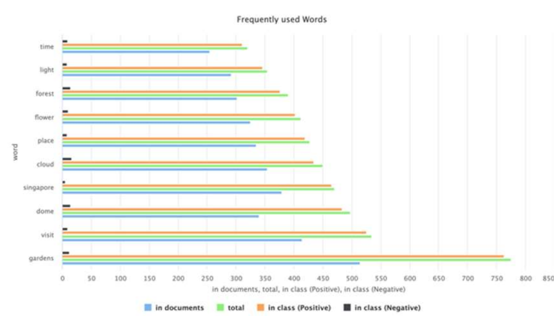

Figure 8: Frequently Used Words in Garden by the Bay Datasets

Figure 8. shows the frequently used words. Analyzing frequently used words reveals significant insights into the semantic attributes associated with the Garden by the Bay destination. The data highlights vital terms such as "gardens" with 514 mentions, "visit" with 414 mentions, "dome" with 340 mentions, "Singapore" with 379 mentions, "cloud" with 354 mentions, and "place" with 335 mentions, indicating recurrent themes in visitor discourse. Notably, references to specific features like "flower" with 325 mentions, "forest" with 302 mentions, and "light" with 292 mentions underscore the diversity of attractions within the site. Moreover, the prominence of "time" with 255 mentions suggests visitors' temporal considerations during the experiences. These findings provide valuable

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insights into visitor engagement and perception within Garden by the Bay, Singapore.

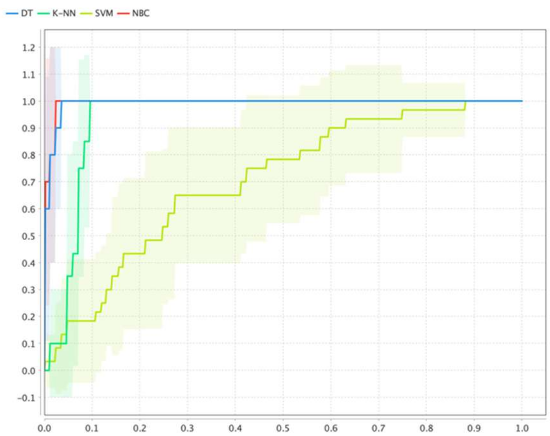

Figure 9: ROC Comparison based on Garden by the Bay Datasets

Figure 9. shows the ROC comparison of NBC, k-NN, DT, and SVM in Garden by the Bay datasets. Based on the data from the Receiver Operating Characteristic (ROC) curve, it is evident that the Naive Bayes Classifier (NBC) demonstrates commendable performance in sentiment classification tasks. The ROC analysis provides valuable insights into the classifier's ability to distinguish between positive and negative sentiments. As indicated by its ROC curve, NBC's robust performance underscores its efficacy in accurately categorizing sentiments within the dataset. Consequently, this underscores NBC's reliability as a viable model for sentiment analysis applications, affirming its suitability for such classification tasks.

Based on the results of the t-test analysis, it is discernible that the probabilities associated with obtaining random values resulting in the observed differences are notably low, with values consistently below the threshold of alpha=0.050. This suggests a high likelihood of a significant difference between the mean values being compared. The list of performance values further illustrates this, with each performance metric displaying a mean value alongside its corresponding standard deviation. Notably, the performance values exhibit narrow confidence intervals, indicating precise estimates of the actual population parameters. Consequently, these findings underscore the statistical significance of the observed differences, affirming the reliability of the t-test results in discerning meaningful disparities among the evaluated metrics.

4.2 Discussion

Sentiment analysis in the tourism sector remains a significant and ongoing challenge, primarily due to the overwhelming amount of unstructured data generated by user reviews on platforms such as TripAdvisor. While stakeholders in the tourism industry are increasingly aware of the importance of customer feedback in shaping business strategies, the vastness of this data often leads to difficulties in extracting meaningful and actionable insights. Reviews are typically lengthy, nuanced, and subjective, making it challenging to translate them into concrete actions that could improve services or customer satisfaction. Consequently, without the right tools and methodologies, tourism businesses risk missing valuable opportunities to optimize their services and respond to customer concerns effectively.

One of the critical problems in sentiment analysis within the tourism context is the imbalance in sentiment classification data. Most reviews tend to skew positive, which makes it harder for traditional machine learning models to detect and analyze negative sentiments. However, negative feedback often contains crucial information for business improvement, as it highlights specific pain points or areas where customer expectations were not met. This imbalance can lead to inaccurate or biased sentiment classification, where models are less effective in recognizing negative comments, ultimately affecting the quality of the insights derived. To address this issue, the study employs the Synthetic Minority Over-sampling Technique (SMOTE), a data-balancing method that ensures models are better equipped to recognize and analyze underrepresented sentiment classes, particularly negative reviews.

The application of the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework further strengthens the research by providing a structured approach to handling complex data analysis tasks. CRISP-DM ensures that the sentiment analysis process is thorough, from the initial understanding of the business context to the deployment of data-driven insights. This methodology allows for a systematic evaluation of sentiment classification models, leading to more reliable and replicable results. Through this approach, the study demonstrates how tourism businesses can more accurately assess visitor feedback, making it easier to implement targeted improvements in service delivery and customer experience.

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In terms of practical implications, this research offers a comprehensive framework for tourism stakeholders to enhance their decision-making processes. By providing a data-driven, systematic way of analyzing customer sentiment, businesses can fine-tune their offerings to meet the evolving expectations of their visitors. In an industry where personalized and memorable experiences are key to maintaining a competitive edge, the ability to glean deep insights from sentiment analysis is invaluable. Moreover, the findings suggest that applying advanced methodologies like SMOTE and CRISP-DM can significantly improve the accuracy of sentiment classification, ensuring that both positive and negative feedback are appropriately considered in service improvements.

Ultimately, this study underscores the importance of leveraging sentiment analysis not only as a reactive tool for understanding customer feedback but also as a proactive measure for driving long-term customer loyalty and satisfaction. As the tourism industry becomes increasingly competitive, especially in a post-pandemic world where traveler preferences are rapidly changing, the ability to respond to feedback effectively and improve service offerings can lead to sustained competitive advantages. This research equips tourism stakeholders with practical tools and methodologies to tackle the persistent challenges in sentiment analysis, offering them a pathway toward enhancing customer satisfaction and driving repeat business.

5. CONCLUSIONS

This research, structured within the CRISP-DM methodology, demonstrates the effectiveness of sentiment classification models, including Naive Bayes (NBC), k-Nearest Neighbors (k-NN), Decision Trees (DT), and Support Vector Machines (SVM), in accurately discerning sentiment polarity in tourism reviews. Comprehensive t-testing reveals significant performance differences, with probabilities ranging from 0.000 to 0.182. The application of SMOTE to address class imbalance has notably improved model accuracy from 0.500 to 0.992, underscoring its importance in refining sentiment classification for unbalanced datasets. These results highlight the critical role sentiment analysis plays in informing strategic decisions in the tourism sector, helping stakeholders better understand visitor feedback and make data-driven improvements to enhance tourist experiences. By integrating the CRISP-DM framework, this study contributes to advancing the application of sentiment analysis in tourism, providing a replicable and structured approach that can be adapted for similar contexts. The findings offer valuable insights for optimizing service delivery, improving tourist satisfaction, and enhancing destination competitiveness in the global tourism market. However, future research should explore additional data sources and more advanced models, such as deep learning, to further refine and expand the practical applications of sentiment analysis in tourism.

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