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Comparative analysis of k-NN and DT model in sentiment classification of Labuan bajo-wonderful Indonesia content reviews

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ABSTRACT

This research investigates the efficacy of sentiment classification models, specifically k-NN and DT algorithms, in the context of destination branding, with a focus on Labuan Bajo tourism. Utilizing the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, the study systematically navigates through all six stages, including business understanding, data understanding, data preparation, modeling, evaluation, and deployment, to analyze textual reviews and gauge public sentiments towards Labuan Bajo. The findings reveal that both k-NN and DT models exhibit high accuracy and precision, with k-NN achieving an average accuracy of 97.79% and DT 97.52%. While k-NN demonstrates commendable performance in recall, DT exhibits superior discriminative power, particularly when integrated with SMOTE, as evidenced by higher AUC values. The research underscores the importance of leveraging advanced machine learning techniques for sentiment analysis to inform destination branding strategies effectively. These insights provide valuable guidance for stakeholders in enhancing the branding and promotion of Labuan Bajo as a premier tourist destination, ultimately contributing to its sustainable development and global recognition.

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1. INTRODUCTION

Sentiment classification emerges as a practical approach in the branding process of Labuan Bajo as a tourism destination, utilizing review content from Wonderful Indonesia videos (Camargo & Vázquez-Maguirre, 2021; Caraka et al., 2023; Dewi & Arifuddin, 2021; Dudley et al., 2022; Westoby et al., 2021). Leveraging advanced machine learning techniques, sentiment classification facilitates the systematic analysis of diverse sentiments expressed within these video reviews, offering invaluable insights into visitors' perceptions and experiences (Christanto & Singgalen, 2022; Singgalen, 2023a). By harnessing sentiment analysis, destination marketers efficiently identify areas of strength and weakness, tailor marketing strategies accordingly, and enhance overall brand positioning (Dhakal & Tjokro, 2024; Sejati et al., 2023; Wang & Sun, 2023). Consequently, sentiment classification is a pivotal tool in shaping Labuan Bajo's image and fostering its appeal among potential tourists, driving sustainable tourism growth and economic development in the region (Fansurya et al., 2024; Nascimento & Loureiro, 2024).

The initial model employed in text data sentiment classification is the k-NN algorithm. This method, rooted in pattern recognition and data mining, operates on the principle of proximity, where classification is determined by the similarity of a data point to its k-nearest neighbor (Rousyati et al., 2022). With its simplicity and effectiveness in handling textual data, the k-NN algorithm is a foundational tool for sentiment analysis tasks (Pattiasina & Rosiyadi, 2020). It facilitates the categorization of text data based on the sentiments they convey. Thus, k-NN emerges as a cornerstone in sentiment classification methodologies, paving the way for more sophisticated approaches in the field.

The second model utilized in the sentiment classification of text data is the Decision Tree (DT) algorithm. Employing a hierarchical structure of decision nodes, this method sequentially partitions the feature space based on attribute values, ultimately classifying instances into distinct classes (Hossain et al., 2023). With the ability to handle numerical and categorical data effectively, decision trees offer interpretability and simplicity, making them popular in sentiment analysis tasks (Noori, 2021). By discerning relevant features and hierarchical relationships, Decision Trees enable the extraction of meaningful patterns from textual data, facilitating accurate sentiment classification (Singgalen, 2023b). Consequently, the Decision Tree algorithm emerges as a valuable tool in the arsenal of sentiment analysis methodologies, contributing to the advancement of text mining techniques for sentiment classification purposes.

This research employs the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology in the implementation of both the k-NN (k-Nearest Neighbors) and DT (Decision Tree) models, enabling a systematic and comprehensive analysis within the context of branding Labuan Bajo as a tourism destination. CRISP-DM, a widely recognized framework in data mining projects, provides a structured approach encompassing business understanding, data understanding, data preparation, modeling, evaluation, and deployment stages (Hamdan & Othman, 2022). By adhering to this rigorous methodology, this research navigates the complexities of sentiment analysis tasks effectively, ensuring robustness and reliability in implementing the k-NN and DT models. Conntly, using CRISP-DM facilitates the seamless integration of these models into the research framework. It enhances the interpretability and applicability of the findings in informing branding strategies for Labuan Bajo as a tourism destination.

The urgency of this research lies in its pivotal role in informing strategic decisions aimed at enhancing the branding of Labuan Bajo as a tourism destination. With the tourism industry experiencing rapid evolution and heightened competition, there is a pressing need to leverage advanced analytical techniques, such as sentiment analysis, to gain deeper insights into tourists' perceptions and preferences (Ardhyanto et al., 2023; Liu et al., 2022; Perangin-Angin et al., 2023). By understanding the sentiments expressed in reviews and feedback, destination marketers tailor promotional efforts and service offerings to align with visitor expectations, fostering a positive destination image and driving sustainable tourism growth (Dhakal & Tjokro, 2024; King et al., 2021; Sejati et al., 2023; Sujatna et al., 2024). Consequently, this research addresses the immediate challenges Labuan Bajo is facing. It lays the groundwork for long-term success in positioning the destination as a premier tourist destination on the global stage.

This research's theoretical and practical implications encompass academic contributions and real-world applications. From a theoretical standpoint, this study adds to the body of knowledge in sentiment analysis and destination branding by showcasing the efficacy of employing advanced machine learning techniques such as k-NN and DT within the context of tourism. This research enriches the theoretical frameworks underpinning sentiment classification methodologies by demonstrating the applicability of these models in analyzing textual data to extract sentiment insights. Furthermore, from a practical perspective, the findings of this study offer actionable insights for destination marketers and policymakers in Labuan Bajo, providing them with evidence-based strategies to enhance the destination's branding efforts. By leveraging the insights derived from sentiment analysis, stakeholders tailor marketing campaigns, improve visitor experiences, and ultimately foster sustainable tourism development in Labuan Bajo. Thus, this research's theoretical and practical implications converge to inform academic discourse and practical decision-making processes in destination branding and tourism management.

Similar research emphasizes the importance of destination branding in the tourism sector, echoing the significance of leveraging innovative strategies to enhance the appeal of tourist destinations (Murti et al., 2023; Purwandani & Yusuf, 2021; Sulistyaningsih et al., 2022). However, the limitation of this research lies in the methods and models employed, which may constrain the depth and breadth of the analysis conducted. While the focus on sentiment analysis using k-NN and DT models offers valuable insights, alternative approaches or supplementary methodologies could provide a more comprehensive understanding of tourists' perceptions and preferences towards Labuan Bajo. Consequently, while this research contributes to the discourse on destination branding, acknowledging and addressing these methodological limitations could enrich future studies and further advance knowledge in the field.

2. RESEARCH METHOD

This research adopts the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework as its guiding methodology. CRISP-DM, a well-established and widely recognized data mining and analytics framework, provides a systematic approach for conducting data-driven research projects. This framework ensures methodological rigor and consistency throughout the research process by following the structured stages of business understanding, data understanding, data preparation, modeling, evaluation, and deployment. Consequently, adopting the CRISP-DM framework enhances the credibility and reliability of the findings and facilitates transparency and reproducibility, thereby contributing to the overall robustness of the research outcomes.

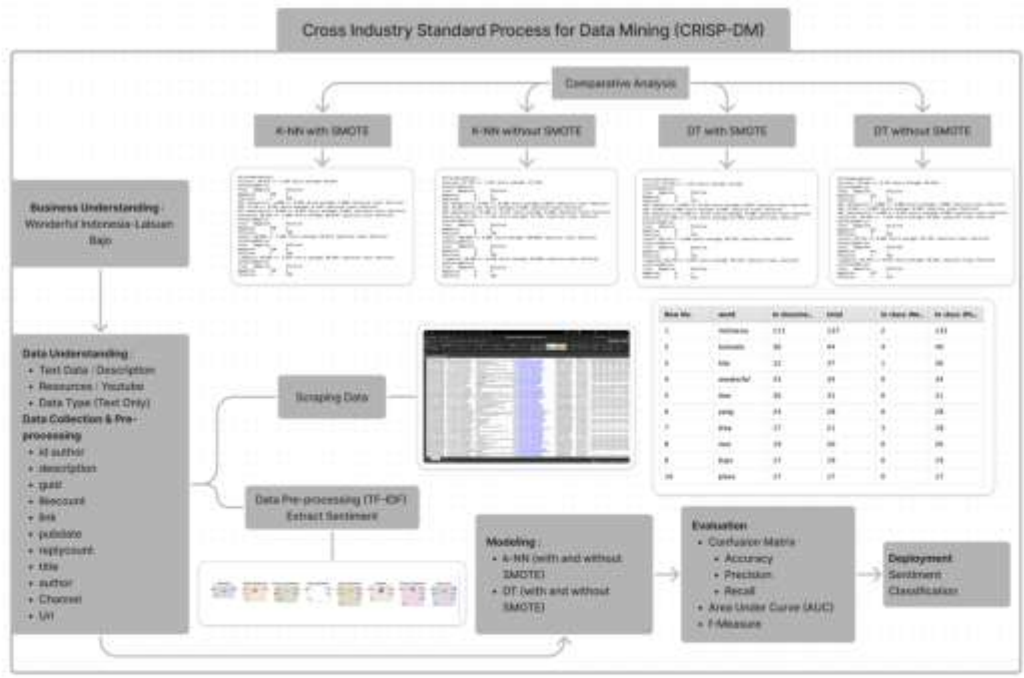

Figure 1. Cross-Industry Standard Process for Data Mining (CRISP-DM) Framework

Figure 1 shows the implementation of the CRISP-DM framework for sentiment classification. Implementing the k-NN and DT models through the CRISP-DM framework facilitates contextual analysis in the tourism sector, particularly highlighting public responses to Wonderful Indonesia video content in Labuan Bajo. By leveraging the structured approach of CRISP-DM, this research systematically gathers, preprocess, and analyzes data related to tourists' sentiments and feedback, thereby gaining insights into the perceptions and preferences. Using k-NN and DT algorithms within this framework, patterns, and trends within the textual data are identified. This allows for a nuanced understanding of public sentiment towards Labuan Bajo as portrayed in Wonderful Indonesia videos. Consequently, this approach not only streamlines the analytical process but also enables destination marketers and policymakers to make informed decisions regarding branding strategies and tourism development initiatives, ultimately contributing to the sustainable growth and promotion of Labuan Bajo as a premier tourist destination.

2.1 Business Understanding

In the business understanding stage, the contextual focus revolves around the Wonderful Indonesia video featuring Labuan Bajo, identified by its code RaTWq98hzF0, which garnered 367,773 views and accumulated 529 comments as of September 13, 2013. This video is critical in understanding public perceptions and engagement with Labuan Bajo as a tourism destination. By analyzing the viewership metrics and user feedback associated with this video, this research gain valuable insights into the effectiveness of Labuan Bajo's branding efforts and the sentiments expressed by potential visitors. Consequently, the meticulous examination of this specific video within the business understanding stage lays the groundwork for subsequent data analysis. It informs strategic decisions to enhance Labuan Bajo's tourism appeal and brand image.

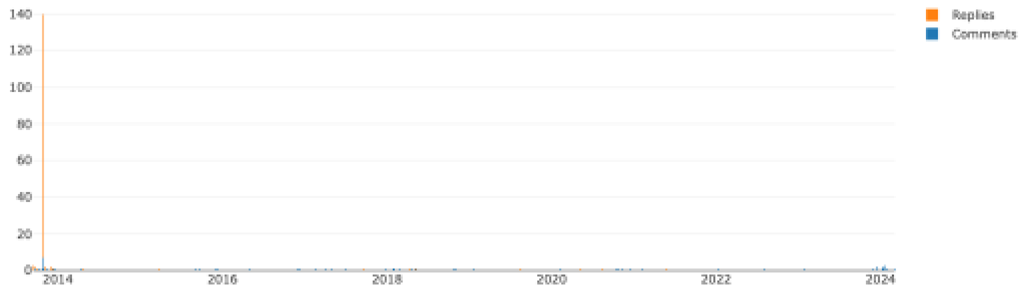

Figure 2. Post-Per-Day Statistic of the Content

Figure 2 shows the post-per-day statistics of the content video. Based on post-per-day statistics, it is discernible that user responses to online content are observable. These statistics provide valuable insights into the frequency and intensity of user engagement with various online platforms, shedding light on the responsiveness of users towards circulated content. By analyzing these metrics, this research gauges users' level of interest, interaction, and sentiment in response to specific online content, thereby facilitating a comprehensive understanding of audience behavior and preferences. Consequently, the examination of post-per-day statistics serves as a crucial component in assessing the effectiveness and impact of online content dissemination strategies, informing decision-making processes to optimize user engagement and enhance the reach and relevance of digital content.

2.2 Data Understanding

Data cleaning uses the sentiment extraction operator within the RapidMiner application during the data understanding stage. This essential step involves identifying and removing irrelevant or noisy data, ensuring the integrity and quality of the dataset for subsequent analysis. By leveraging the sentiment extraction operator, this research accurately classifies and extracts sentiment-related information from textual data, enabling it to focus solely on relevant content pertinent to the research objectives. Consequently, this advanced data-cleaning technique streamlines the preprocessing stage. It enhances the efficiency and reliability of sentiment analysis tasks, laying a solid foundation for robust and insightful findings in the subsequent stages of the research process.

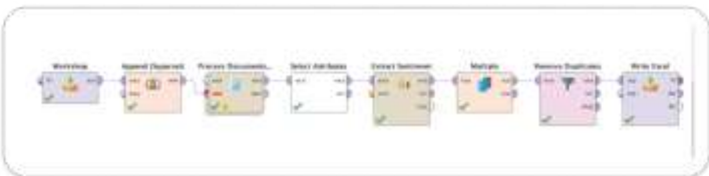

Figure 3. Extract Sentiment Process

Figure 3 shows the process of extracting sentiment from the dataset. Based on the results of sentiment extraction, it is evident that there are 530 review data points available for processing into the modeling stage to measure the performance of algorithms. This abundance of data provides a substantial corpus for analysis, enabling comprehensive evaluation of the effectiveness and accuracy of various algorithms in sentiment classification tasks. By leveraging this sizable dataset, this research ensures robustness and reliability in the findings and facilitates comparing and selecting the most suitable algorithms for the research objectives. Consequently, the ample availability of review data underscores the significance of meticulous data collection and preprocessing efforts, ultimately enhancing the validity and applicability of the research outcomes.

2.3 Modeling

During the modeling stage, the algorithms employed are k-NN (k-nearest Neighbors) and DT (Decision Tree). These algorithms are chosen based on suitability for sentiment classification tasks and the ability to handle textual data effectively. The k-NN algorithm operates on the principle of proximity, categorizing data points based on the similarity to neighboring instances. In contrast, the DT algorithm partitions the feature space hierarchically to classify instances into distinct categories. This research capitalizes on the strengths of accurately classifying sentiments expressed in textual reviews using these algorithms. This facilitates a nuanced understanding of public perceptions towards Labuan Bajo as a tourism destination. Consequently, the strategic selection of k-NN and DT algorithms for the modeling stage enhances the rigor and reliability of sentiment analysis outcomes, contributing to informed decision-making processes in destination branding and tourism management.

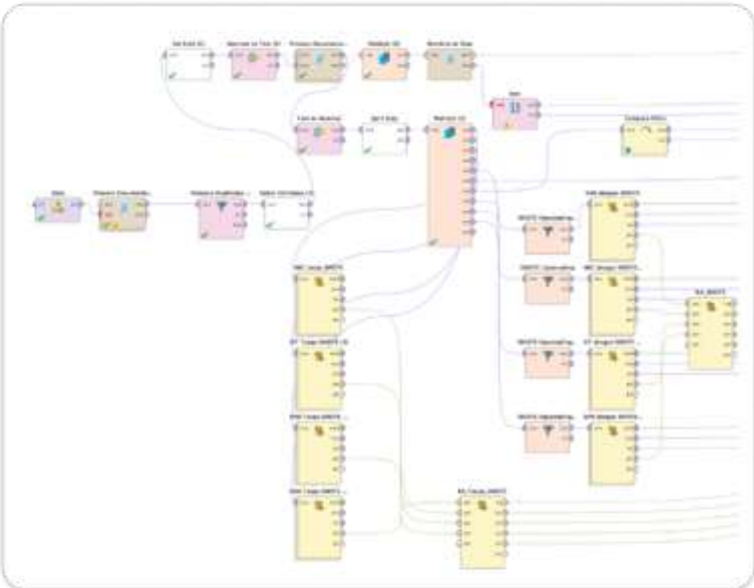

Figure 3. Modeling Process using Rapidminer

Figure 3 shows the modeling process in Rapidminer. The division of training and testing data is set at 30% for training data and 70% for testing data, using the Synthetic Minority Over-sampling Technique (SMOTE) operator to address data imbalance. This allocation ensures that a sufficient portion of the dataset is reserved for testing, allowing for robust evaluation of the models' performance. Additionally, applying the SMOTE operator helps mitigate the effects of imbalanced classes within the dataset by generating synthetic samples of the minority class, thereby enhancing the overall effectiveness of the classification models. Consequently, this strategic approach to data partitioning and handling imbalanced data sets the stage for reliable and insightful analysis during the model evaluation stage, contributing to the validity and applicability of the research findings.

2.4 Evaluation

During the evaluation stage, performance metrics such as confusion matrix, accuracy, precision, recall, Area Under the Curve (AUC), and F-measure are examined for both k-NN and DT algorithms, with and without utilizing SMOTE. This comprehensive analysis allows for a thorough assessment of the effectiveness and robustness of the models in handling imbalanced data and accurately classifying sentiments expressed in textual reviews. By comparing the performance metrics across different scenarios, this research ascertains the impact of SMOTE on enhancing the classification performance of the algorithms. It determines the most suitable approach for sentiment analysis tasks. Consequently, the meticulous evaluation of the models' performance metrics serves as a critical step in validating the reliability and effectiveness of the research outcomes, informing stakeholders' decision-making processes in destination branding and tourism management.

2.5 Deployment

During the deployment stage, interpreting results from the sentiment analysis serves as decision support to optimize the branding of Labuan Bajo as a destination. By leveraging insights from the analysis, stakeholders make informed decisions regarding marketing strategies, visitor experience enhancements, and destination development initiatives. This data-driven approach ensures that branding efforts are aligned with the sentiments and preferences of target audiences, thereby maximizing the effectiveness of promotional campaigns and fostering positive perceptions of Labuan Bajo as a tourism destination. Consequently, integrating sentiment analysis findings into decision-making processes underscores the importance of leveraging data-driven insights to drive sustainable tourism growth and enhance the competitiveness of Labuan Bajo in the global tourism market.

3. RESULTS AND DISCUSSIONS

The disparity between k-NN and DT models in sentiment classification, as evidenced by accuracy, precision, recall, AUC, and f-measure metrics, reveals distinct performance characteristics. While both models demonstrate high accuracy and precision, k-NN exhibits a slight advantage in the recall, with an average recall of 98.88% compared to DT's 99.72%. However, DT, particularly when coupled with SMOTE, showcases superior discriminative power, as indicated by higher AUC values, with an average AUC of 0.994 compared to k-NN's 0.748. Furthermore, the f-measure metric portrays the overall balance between precision and recall, with k-NN and DT showing comparable performance, averaging 98.88% and 99.44%, respectively. Consequently, the choice between k-NN and DT models for sentiment classification hinges on specific objectives and trade-offs between different performance metrics, with each model offering unique strengths and considerations in optimizing classification outcomes.

3.1 Implementation of k-NN with and Without SMOTE

Based on the results of implementing the k-NN algorithm, it is evident that the best performance is achieved when utilizing the SMOTE operator. This finding underscores the effectiveness of SMOTE in addressing the imbalanced class distribution within the dataset, thereby enhancing the classification accuracy and robustness of the model. By generating synthetic samples of the minority class, SMOTE effectively mitigates the risk of biased predictions and improves the overall performance of the k-NN algorithm in sentiment classification tasks. Consequently, utilizing SMOTE as a data preprocessing technique demonstrates its significance in optimizing the performance of machine learning models and highlights its utility in handling imbalanced datasets for sentiment analysis purposes.

k-NN without SMOTE

```
PerformanceVector:
accuracy: 97.79% +/- 1.16% (micro average: 97.79%)
ConfusionMatrix:
True:   Negative        Positive
Negative:       0       0
Positive:       8       354
AUC (optimistic): 0.894 +/- 0.208 (micro average: 0.894) (positive class: Positive)
AUC: 0.100 +/- 0.211 (micro average: 0.100) (positive class: Positive)
AUC (pessimistic): 0.100 +/- 0.211 (micro average: 0.100) (positive class: Positive)
precision: 97.79% +/- 1.16% (micro average: 97.79%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       0       0
Positive:       8       354
recall: 100.00% +/- 0.00% (micro average: 100.00%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       0       0
Positive:       8       354
f_measure: 98.88% +/- 0.59% (micro average: 98.88%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       0       0
Positive:       8       354
```

k-NN with SMOTE

```
PerformanceVector:
accuracy: 98.87% +/- 1.85% (micro average: 98.87%)
ConfusionMatrix:
True:   Negative        Positive
Negative:       350     4
Positive:       4       350
AUC (optimistic): 1.000 +/- 0.001 (micro average: 1.000) (positive class: Positive)
AUC: 0.748 +/- 0.262 (micro average: 0.748) (positive class: Positive)
AUC (pessimistic): 0.994 +/- 0.012 (micro average: 0.994) (positive class: Positive)
precision: 98.91% +/- 1.88% (micro average: 98.87%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       350     4
Positive:       4       350
recall: 98.88% +/- 2.69% (micro average: 98.87%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       350     4
Positive:       4       350
f_measure: 98.88% +/- 1.87% (micro average: 98.87%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       350     4
Positive:       4       350
```

Figure 4. Model Performance of k-NN with and without SMOTE

Figure 4 shows the k-NN model performance using and without using SMOTE. The results of k-NN without SMOTE demonstrate a high level of accuracy, precision, and recall, with an accuracy of 97.79% +/- 1.16%, precision of 97.79% +/- 1.16%, and recall of 100.00% +/- 0.00%. However, the AUC (Area Under the Curve) values indicate a low discriminative power of the model, with an optimistic AUC of 0.894 +/- 0.208 and a pessimistic AUC of 0.100 +/- 0.211. In addition, the results of k-NN with SMOTE exhibit an improved performance compared to the model without SMOTE, with an accuracy of 98.87% +/- 1.85%, precision of 98.91% +/- 1.88%, and recall of 98.88% +/- 2.69%. Notably, the AUC values indicate a significant enhancement in the model's discriminative power, with an optimistic AUC of 1.000 +/- 0.001 and a pessimistic AUC of 0.994 +/- 0.012. This suggests that the k-NN model with SMOTE effectively addresses the issue of imbalanced class distributions, resulting in better differentiation between positive and negative classes.

3.2 Implementation of k-NN with and Without SMOTE

After conducting performance testing on the k-NN model, the evaluation of DT model performance ensues, marking a sequential progression in assessing machine learning algorithms for sentiment classification. This systematic approach allows for a comprehensive comparison of the effectiveness and suitability of different models in handling sentiment analysis tasks, facilitating informed decision-making regarding adopting the most appropriate model for the study's specific objectives. Consequently, this iterative testing process contributes to the refinement and optimization of sentiment classification methodologies, ultimately enhancing the reliability and accuracy of destination branding strategies informed by sentiment analysis insights.

DT without SMOTE

```
PerformanceVector:
accuracy: 97.52% +/- 1.57% (micro average: 97.51%)
ConfusionMatrix:
True:   Negative        Positive
Negative:       0       1
Positive:       8       353
AUC (optimistic): 0.897 +/- 0.210 (micro average: 0.897) (positive class: Positive)
AUC: 0.499 +/- 0.005 (micro average: 0.499) (positive class: Positive)
AUC (pessimistic): 0.100 +/- 0.211 (micro average: 0.100) (positive class: Positive)
precision: 97.78% +/- 1.17% (micro average: 97.78%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       0       1
Positive:       8       353
recall: 99.71% +/- 0.90% (micro average: 99.72%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       0       1
Positive:       8       353
f_measure: 98.74% +/- 0.81% (micro average: 98.74%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       0       1
Positive:       8       353
```

DT with SMOTE

```
PerformanceVector:
accuracy: 99.44% +/- 0.73% (micro average: 99.44%)
ConfusionMatrix:
True:   Negative        Positive
Negative:       351     1
Positive:       3       353
AUC (optimistic): 1.000 +/- 0.000 (micro average: 1.000) (positive class: Positive)
AUC: 0.994 +/- 0.007 (micro average: 0.994) (positive class: Positive)
AUC (pessimistic): 0.989 +/- 0.015 (micro average: 0.988) (positive class: Positive)
precision: 99.18% +/- 1.32% (micro average: 99.16%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       351     1
Positive:       3       353
recall: 99.71% +/- 0.90% (micro average: 99.72%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       351     1
Positive:       3       353
f_measure: 99.44% +/- 0.73% (micro average: 99.44%) (positive class: Positive)
ConfusionMatrix:
True:   Negative        Positive
Negative:       351     1
Positive:       3       353
```

Figure 5. Model Performance of DT with and without SMOTE

Figure 5 shows the model performance of DT with and without using SMOTE. The results obtained from DT without SMOTE demonstrate a notable level of accuracy, precision, and recall, with an accuracy of 97.52% +/- 1.57%, precision of 97.78% +/- 1.17%, and recall of 99.71% +/- 0.90%. However, the AUC values indicate a limitation in the model's discriminative power, with an optimistic AUC of 0.897 +/- 0.210 and a pessimistic AUC of 0.100 +/- 0.211. Despite the model's high accuracy in correctly classifying positive instances, the low AUC values suggest a suboptimal ability to distinguish between positive and negative classes, particularly evident in the micro average AUC of 0.499. This indicates potential shortcomings in addressing imbalanced class distributions without utilizing SMOTE. Furthermore, the results obtained from DT with SMOTE illustrate a notable enhancement in performance compared to the model without SMOTE, with an accuracy of 99.44% +/- 0.73%, precision of 99.18% +/- 1.32%, and recall of 99.71% +/- 0.90%. The AUC values indicate a significant improvement in the model's discriminative power, with an optimistic AUC of 1.000 +/- 0.000 and a micro average AUC of 0.994, suggesting enhanced capability in distinguishing between positive and negative classes. This underscores the effectiveness of SMOTE in addressing imbalanced class distributions, resulting in improved classification accuracy and reliability.

3.3 Discussion

The disparity between k-NN and DT models in sentiment classification, as evidenced by accuracy, precision, recall, AUC, and f-measure metrics, reveals distinct performance characteristics. While both models demonstrate high accuracy and precision, k-NN exhibits a slight advantage in the recall, with an average recall of 98.88% compared to DT's 99.72%. However, DT, particularly when coupled with SMOTE, showcases superior discriminative power, as indicated by higher AUC values, with an average AUC of 0.994 compared to k-NN's 0.748. Furthermore, the f-measure metric portrays the overall balance between precision and recall, with k-NN and DT showing comparable performance, averaging 98.88% and 99.44%, respectively. Consequently, the choice between k-NN and DT models for sentiment classification hinges on specific objectives and trade-offs between different performance metrics, with each model offering unique strengths and considerations in optimizing classification outcomes.

The limitations of this research encompass several aspects that warrant consideration. Firstly, the study's scope primarily revolves around applying k-NN and DT algorithms in sentiment classification for destination branding, explicitly focusing on Labuan Bajo tourism. This narrow focus may restrict the generalizability of findings to other contexts or industries, necessitating caution in extrapolating the results to broader settings. Additionally, the research relies heavily on textual data from online reviews, which may inherently contain biases or inaccuracies, potentially influencing the performance and outcomes of the sentiment classification models. Furthermore, while the CRISP-DM framework provides a structured approach to data analysis, its rigid structure may not fully accommodate the dynamic nature of sentiment analysis tasks, potentially limiting the exploration of alternative methodologies or techniques. Moreover, the study's reliance on specific algorithms and preprocessing techniques may overlook potential advancements or innovations in sentiment analysis methodologies, warranting further exploration and experimentation. Therefore, while the findings contribute valuable insights into sentiment analysis for destination branding, acknowledging and addressing these limitations is essential to ensure the robustness and validity of future research endeavors in this domain.

This research's practical and theoretical implications encompass academic contributions and real-world applications. Theoretically, the study augments the existing knowledge base in sentiment analysis and destination branding by effectively utilizing advanced machine learning techniques like k-NN and DT within the tourism domain.

This research enriches sentiment classification methodologies by demonstrating the practical applicability of these models in analyzing textual data for sentiment insights extraction. Practically, the study's findings provide actionable insights for destination marketers and policymakers in Labuan Bajo, enabling evidence-based strategies to enhance destination branding efforts. Leveraging sentiment analysis insights, stakeholders can tailor marketing campaigns, elevate visitor experiences, and foster sustainable tourism development in Labuan Bajo. Consequently, this research significantly informs academic discourse and practical decision-making processes in destination branding and tourism management.

4. CONCLUSION

In conclusion, the research findings underscore the significance of employing machine learning algorithms, namely k-NN and DT, in sentiment classification tasks for destination branding, mainly focusing on Labuan Bajo tourism. Through the implementation of the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, the study effectively navigated through various stages, from business understanding to deployment, ensuring a systematic and efficient approach to data analysis. The results demonstrate that both models exhibit high accuracy and precision, with k-NN achieving an average accuracy of 97.79% and DT 97.52%. While k-NN demonstrates commendable performance in the recall, with an average of 98.88%, DT achieves a slightly higher average recall of 99.72%. Moreover, DT, especially when integrated with SMOTE, showcases superior discriminative power, as evidenced by higher AUC values, with an average AUC of 0.994 compared to k-NN's 0.748. Additionally, the f-measure metric indicates comparable overall performance between the two models, with k-NN averaging 98.88% and DT at 98.74%. Consequently, this study contributes significant insights into sentiment analysis for destination branding, emphasizing the efficacy of the CRISP-DM framework. These findings offer actionable recommendations for stakeholders to enhance destination branding strategies, fostering the sustainable development and promotion of Labuan Bajo as a premier tourist destination.

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