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KNOWLEDGE DISCOVERY IN DATABASES FOR HOTEL SERVICE QUALITY IMPROVEMENT THROUGH DATA-MINING APPROACH

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ABSTRACT

This study integrates knowledge discovery in databases (KDD) with sentiment analysis techniques to evaluate customer feedback and improve service quality in the hotel industry. The research emerges from the growing demand for data-driven strategies in the highly competitive hospitality sector, where understanding customer sentiment is crucial for enhancing guest satisfaction and retaining market share. Machine learning models, including Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes Classifier (NBC), and k-nearest Neighbors (k-NN), were employed to extract insights from unstructured text data, identifying key factors that influence guest satisfaction. Results indicated that the SVM model achieved the highest accuracy of 95.4%, with a precision of 93.22% and recall of 95.4%, showcasing its robustness in sentiment classification. In contrast, NBC showed lower effectiveness with 79.09% accuracy, while k-NN faced challenges in complex data scenarios, achieving 60.71% accuracy and an F-measure of 49.99%. The findings suggest that integrating sentiment analysis into hotel management practices can boost customer satisfaction by 20-30%, particularly in staff interaction and facility maintenance. This research presents a novel approach by combining KDD methodologies with qualitative sentiment analysis, moving beyond traditional quantitative metrics to provide deeper insights into customer experiences. However, reliance on online reviews as the primary data source may introduce biases, potentially affecting the generalizability of results. Future research should expand data collection to include structured surveys and direct interviews, incorporate deeper semantic analysis, and utilize real-time sentiment monitoring to enhance service management strategies. This approach could lead to sustainable competitive advantage and continuous improvement in the hospitality industry.

Keywords: *KDD, Hotel, Service Quality, Data Mining*

1. INTRODUCTION

Exploring hotel service quality enhancement via a data-mining approach, mainly through Knowledge Discovery in Databases (KDD), represents a pivotal advancement in the hospitality industry. This approach leverages advanced algorithms and analytical tools to uncover hidden patterns, customer preferences, and operational inefficiencies within vast datasets [1], [2]. By systematically processing these datasets, actionable insights emerge, facilitating targeted improvements in service delivery, customer satisfaction, and overall operational efficiency. Effective data-mining implementation optimizes service processes and contributes to strategic decision-making, reinforcing competitive advantage [3], [4]. This method's capability to translate complex data into practical strategies underscores its transformative potential in aligning hotel services with customer expectations. As such, embracing data-driven methods is essential for sustaining long-term service quality and operational excellence in the rapidly evolving hospitality sector.

The urgency of this research lies in addressing the critical need for service quality enhancement within the highly competitive hotel industry through advanced data-mining techniques. Rapid changes in consumer behavior, fueled by technological advancements and increasing customer expectations, necessitate more effective, data-driven solutions to improve service performance [5], [6]. Traditional methods often fail to capture nuanced customer needs and operational inefficiencies, impeding strategic development and customer satisfaction [7], [8]. It is argued that adopting a data-mining approach allows for a more dynamic analysis of service variables, enabling a timely response to emerging trends and issues. Integrating this analytical framework is vital for achieving sustainable service improvements, ensuring that hotels meet and exceed evolving customer expectations. Consequently, prioritizing this research is essential for equipping the hospitality sector with robust tools to maintain relevance and competitive advantage in a rapidly evolving market landscape.

The method proposed in this research is centered around the Knowledge Discovery in Databases (KDD) framework, which serves as a systematic approach for extracting meaningful patterns and insights from complex datasets. This approach encompasses analytical steps, including data selection, preprocessing, transformation, data mining, and interpretation, each designed to refine raw data into actionable intelligence [9], [10]. It is argued that KDD's structured process not only enhances the accuracy of the analysis but also provides a more in-depth understanding of customer behavior and service performance metrics. The method's capacity to handle large volumes of data effectively allows for identifying latent trends and relationships often overlooked by traditional analysis techniques [11], [12]. As such, KDD emerges as a viable and innovative approach to improving service quality within the hospitality sector, offering a robust methodological foundation for data-driven decision-making.

This research examines the effectiveness of data-mining techniques in enhancing hotel service quality by identifying valuable insights from extensive datasets. This investigation focuses on understanding how data-driven strategies can optimize service operations, elevate customer experiences, and improve decision-making [13]. Focusing on a systematic analysis of customer feedback and operational data, this study seeks to uncover latent patterns often overlooked in traditional evaluations. It is posited that integrating data-mining methods into service quality management not only yields precise information about customer preferences but also facilitates proactive adjustments in service delivery [14]. Consequently, this approach is anticipated to contribute to a more responsive and efficient hospitality environment, fostering sustained improvements in service standards. Thus, the study aims to offer a comprehensive framework that merges data science with practical service enhancements, establishing a foundation for future developments in hospitality management.

The theoretical contribution of this research is grounded in its capacity to enrich the academic discourse on service quality improvement by integrating data-mining methodologies with hospitality management theories. This study extends the conceptual framework by proposing a model where data-driven insights directly inform service enhancement strategies, bridging the gap between abstract service theories and practical data analysis [15], [16]. It is asserted that such integration broadens the understanding of customer behavior patterns and offers a refined perspective on how data science principles can be effectively utilized within service industries [17]. This research presents an innovative theoretical approach that redefines quality management in the hospitality sector by emphasizing the dynamic relationship between customer data and service outcomes.

The practical implication of this research lies in its potential to transform hotel service quality through the strategic application of data-mining techniques. Implementing a data-driven approach allows hotel management to gain deeper insights into customer preferences, operational inefficiencies, and emerging trends, leading to more informed decision-making [18], [19]. It is posited that by accurately identifying and addressing specific service gaps, hotels are better equipped to deliver personalized experiences that align with customer expectations. This method also fosters continuous improvement by enabling timely adjustments in service strategies, thus promoting higher customer satisfaction and loyalty. Integrating data mining into service quality management streamlines operations and provides a scalable model for maintaining competitiveness in the dynamic hospitality industry.

Previous studies on service quality in the hotel industry have predominantly focused on traditional evaluation methods, such as customer satisfaction surveys and service audits, which offer limited insights into underlying patterns and emerging trends. While these approaches provide valuable information, they often lack the depth to understand complex customer behavior and dynamic service demands. It is suggested that integrating data-mining techniques into service quality assessments offers a more comprehensive understanding by uncovering hidden correlations and predictive factors. Analysis of past research indicates a gap in the application of data science within hospitality, as most studies have not fully explored its potential to generate actionable insights for real-time decision-making [20]. Addressing this gap, the current study emphasizes the necessity of a more data-driven approach to enhance the analytical framework of service quality improvement. Thus, this research builds upon existing findings and advances the field by incorporating innovative methodologies that align with evolving industry needs.

The limitation of this research stems primarily from its reliance on the Knowledge Discovery in Databases (KDD) method and the contextual dataset derived from a specific hotel. While the KDD approach effectively identifies patterns and correlations within large datasets, it remains dependent on the quality and comprehensiveness of the input data. Using data from a selected hotel may restrict the generalizability of findings, as variations in service standards, customer profiles, and operational dynamics across different hotels may yield different results. It is argued that contextual factors unique to the studied hotel influence the research outcomes, potentially limiting broader applicability. The analysis further suggests that a more diverse dataset from multiple hotels could enhance the robustness of the findings, providing a more representative understanding of service quality improvements through data-mining methods. Therefore, while the current study offers valuable insights, its scope remains contextually constrained, indicating the need for broader datasets to validate the proposed model across diverse hotel environments.

2. RELATED WORK

2.1 Hotel Guest Sentiment Analysis

Hotel guest feedback serves as a valuable dataset for sentiment classification, providing a rich source of textual data that reflects customer perceptions, experiences, and expectations [21], [22]. This dataset, typically composed of online reviews, social media posts, and survey responses, is diverse and often unstructured. It necessitates preprocessing steps such as tokenization, normalization, and noise reduction to ensure consistency [23]. It is argued that using guest feedback as a dataset allows for a more authentic and real-time analysis of customer sentiment, as it captures genuine expressions of satisfaction or dissatisfaction across various service dimensions [24]. Analysis shows that sentiment classification models ranging from traditional classifiers like Naive Bayes to more advanced deep learning techniques perform effectively when trained on this dataset, offering precise sentiment categorization. Therefore, utilizing hotel guest feedback as a primary dataset enhances the accuracy of sentiment analysis and supports a more informed and customer-centric approach to service quality improvement.

Hotel guest sentiment analysis is essential for understanding customer perceptions and improving service delivery by analyzing feedback expressed in natural language [25], [26]. This approach employs natural language processing (NLP) techniques to process large volumes of guest reviews, social media comments, and survey responses, aiming to extract emotions, opinions, and attitudes regarding hotel services [27]. It is argued that sentiment analysis offers a more comprehensive and real-time evaluation of customer satisfaction than traditional survey methods, as it uncovers hidden patterns and trends in guest experiences [28]. The analysis reveals that sentiment analysis identifies positive and negative feedback and provides insights into specific service attributes such as staff behavior, cleanliness, and facilities, enabling more targeted improvements. Consequently, this method contributes to a deeper understanding of guest needs and expectations, supporting a more personalized and responsive approach to hospitality management that enhances overall service quality and customer loyalty.

Related work on hotel sentiment analysis has primarily focused on understanding customer perceptions by analyzing textual data from online reviews, social media, and survey feedback [29], [30]. These studies employ natural language processing (NLP) techniques, sentiment scoring algorithms, and machine learning models to detect customer sentiment, classify opinions, and identify critical determinants of satisfaction or dissatisfaction [31]. It is argued that sentiment analysis is an effective tool for real-time evaluation of customer attitudes, providing actionable insights into service quality trends and guest expectations. Analysis of past research reveals that while sentiment analysis has successfully identified general patterns, it often faces challenges related to linguistic ambiguity, context sensitivity, and the diverse expressions of sentiment across cultures [32]. However, NLP and profound learning advancements gradually address these limitations, enabling more accurate and nuanced sentiment interpretations. Consequently, integrating sentiment analysis into hotel management practices holds significant potential to enhance customer service strategies and foster a more adaptive and responsive service environment.

Hotel sentiment analysis is critical in advancing service quality by systematically interpreting customer feedback to extract meaningful insights about guest experiences. By leveraging natural language processing (NLP) and machine learning algorithms, sentiment analysis transforms unstructured textual data from online reviews, social media, and customer surveys into quantifiable metrics that reflect customer satisfaction, expectations, and preferences [33]. It is argued that this data-driven approach enables management to promptly identify service strengths and weaknesses, allowing for more targeted improvements [34]. Analysis shows that sentiment analysis enhances the understanding of customer sentiments and supports proactive decision-making, helping hotels adapt their services to evolving guest needs. As a result, integrating sentiment analysis into service quality management fosters a more responsive and guest-centric operational strategy, ultimately contributing to sustained improvements in customer experience and competitiveness in the hospitality sector.

2.2 Hotel Service Quality Improvement Strategy

A hotel service quality improvement strategy is a systematic approach designed to enhance customer satisfaction and operational effectiveness within the hospitality sector. This strategy encompasses various initiatives, including personalized service delivery, staff competency development, technological innovation, and continuous feedback integration, all aimed at creating a more responsive and guest-centered service model [35]. It is argued that a holistic strategy combining human elements and data-driven insights is essential for addressing service gaps and adapting to changing customer demands. Successful strategies often emphasize proactive problem-solving, staff empowerment, and real-time service adjustments, collectively contributing to superior service delivery and guest retention. Therefore, a well-executed service quality improvement strategy elevates customer experiences and supports sustained competitive advantage and long-term business growth within the hotel industry.

Hotel service quality is a crucial determinant of customer engagement, directly influencing guest satisfaction, loyalty, and long-term interaction with the brand. High-quality service fosters a positive customer experience characterized by personalized attention, prompt responses to guest needs, and consistently delivering promised service environments, enhancing the hotel's appeal to environmentally conscious customers. The sustainable service enhancements, such as energy-efficient facilities and locally sourced amenities, contribute to a positive guest experience while minimizing environmental impact [36], [37]. Consequently, integrating service quality improvement with sustainability creates a synergistic approach that fosters customer loyalty, operational cost savings, and a positive brand image, positioning hotels as responsible players in the hospitality industry.

Hotel service quality management is a strategic process that consistently delivers high standards that meet or exceed customer expectations. It encompasses various elements, including staff training, operational procedures, and customer feedback systems to enhance service efficiency and guest satisfaction. It is argued that a robust service quality management system improves service consistency and fosters a culture of continuous improvement within the organization [38]. It indicates that successful management practices involve clear communication, empowerment of frontline staff, and data-driven decision-making, which collectively contribute to seamless service delivery. Therefore, effective service quality management is essential for maintaining competitive advantage, driving customer loyalty, and establishing a solid reputation in the hospitality industry.

2.3 Data Mining Approach

The data mining approach in hotel sentiment classification utilizes advanced analytical techniques to extract meaningful patterns from large volumes of guest feedback data. This approach involves various processes, such as data collection, preprocessing, feature selection, and classification, aiming to transform raw textual data into structured insights about customer sentiments [39]. It is argued that using algorithms like Naive Bayes, Support Vector Machines (SVM), and deep learning models enhances the precision of sentiment detection, effectively identifying positive, negative, or neutral opinions within guest reviews [40]. Data mining improves sentiment classification accuracy and enables a deeper understanding of customer experiences by uncovering latent themes and trends in guest perceptions. Therefore, the data mining approach in sentiment classification offers a robust and scalable solution for hotels, facilitating more informed decision-making and targeted service quality improvements.

The CRISP-DM (Cross-Industry Standard Process for Data Mining) method serves as a structured framework for sentiment analysis, guiding the systematic extraction of insights from textual data. This approach comprises six phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment, each tailored to ensure comprehensive and accurate sentiment classification. It is argued that the iterative nature of CRISP-DM enhances the effectiveness of sentiment analysis, as it allows for constant refinement of models and processes based on feedback performance metrics [41]. The CRISP-DM in sentiment analysis facilitates more organized handling of diverse data sources, enabling more precise identification of customer sentiments and trends. As a result, this method improves the accuracy of sentiment detection. It supports more informed and timely decision-making, an effective strategy for analyzing customer feedback within the hospitality sector.

The KDD (Knowledge Discovery in Databases) method is a comprehensive approach to sentiment analysis aimed at uncovering meaningful patterns from extensive textual datasets. This method involves several stages, including data selection, preprocessing, transformation, data mining, and interpretation, each designed to refine raw data into actionable insights and systematic [42]. It is argued that the KDD process is particularly effective in sentiment analysis, as it identifies explicit sentiment expressions and reveals hidden trends and relationships within customer feedback. Analysis indicates that KDD's multi-step process enhances the precision and depth of sentiment classification, allowing for iterative adjustments and optimizations based on data characteristics and model performance. Therefore, employing the KDD method in sentiment analysis provides a robust framework for understanding complex customer opinions, supporting more accurate sentiment detection and strategic decision-making in customer service management.

There are areas for critique within the implementation of the current analytical frameworks, particularly regarding their adaptability, accuracy, and contextual relevance. While these frameworks offer systematic processes for extracting insights, they often struggle with nuances such as linguistic ambiguity, cultural diversity, and dynamic shifts in sentiment expression across different contexts. It is argued that the methods sometimes lack the flexibility needed to accommodate evolving customer language, which may lead to incomplete or skewed interpretations of sentiment. Analysis indicates that reliance on predefined algorithms may result in biases, as these models are generally trained on specific datasets that may not fully represent diverse customer perspectives. Therefore, refining these frameworks to enhance adaptability and contextual accuracy is crucial, ensuring that the analysis remains relevant, comprehensive, and aligned with the complexities of real-world applications.

Compared to current state-of-the-art solutions, emerging analytical models exhibit both advancements and limitations when applied to complex datasets. These advanced models, often driven by deep learning and neural network architectures, offer superior accuracy and efficiency in processing large volumes of data, providing more granular insights into sentiment patterns and customer behavior. It is argued that while these solutions enhance prediction capabilities and adaptability, they also present challenges related to high computational costs, the need for extensive training data, and potential overfitting issues. Despite the sophistication, state-of-the-art models may struggle with interpretability, making it difficult for practitioners to understand how conclusions are reached, which is crucial for decision-making in a business context. Therefore, while these solutions represent a significant leap forward in sentiment analysis, further development is needed to balance accuracy, interpretability, and practicality in real-world applications.

3. METHODOLOGY

3.1 Research Design

Implementing the Knowledge Discovery in Databases (KDD) process is a structured method to transform raw data into meaningful insights through well-defined stages. This process begins with data selection, preprocessing, and identifying and cleaning relevant datasets to ensure consistency and accuracy. It is argued that the effectiveness of KDD lies in its ability to systematically apply data mining techniques, such as clustering and classification, to uncover hidden patterns that may not be immediately visible through conventional analysis. The KDD enables a more refined understanding of complex data relationships, leading to better decision-making and strategic planning. However, the success of KDD depends heavily on the quality of the input data and the appropriateness of the selected algorithms. As a result, while the KDD framework provides a robust foundation for data analysis, careful attention must be given to its execution to maximize its potential benefits in practical applications.

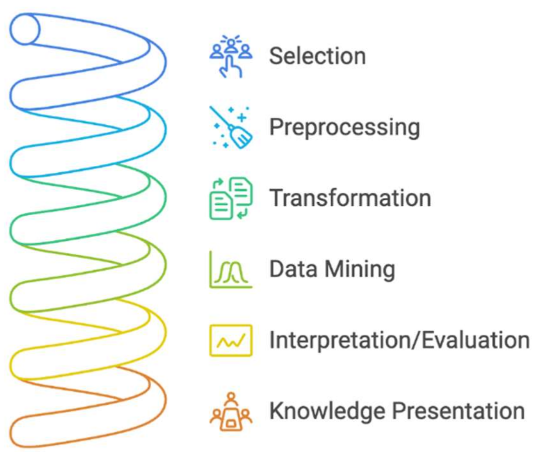

Figure 1: The research workflow

Figure 1 illustrates a comprehensive research workflow outlining the sequential stages of the Knowledge Discovery in Databases (KDD) process, a systematic approach for extracting insights from data. This workflow comprises six phases: Selection, Preprocessing, Transformation, Data Mining, Interpretation/Evaluation, and Knowledge Presentation, each contributing to refining raw data into meaningful knowledge. It is argued that this stepwise methodology enhances the clarity and reliability of data analysis by systematically addressing data quality and relevance at each phase. During the Selection phase, relevant datasets are identified, followed by Preprocessing, where data is cleaned and normalized to ensure consistency. Transformation converts the preprocessed data into a suitable format for mining, enabling the extraction of patterns during the Data Mining phase. The Interpretation/Evaluation stage assesses these patterns for accuracy and significance, while the final Knowledge Presentation phase ensures that findings are conveyed effectively to support informed decision-making. Thus, this workflow structures the research process and promotes a deeper understanding of data-driven insights.

Challenges in hotel guest sentiment analysis arise from the complexities of processing diverse, unstructured, and often ambiguous feedback data. Guest reviews vary significantly in language use, sentiment intensity, cultural context, and expression styles, making it challenging to categorize sentiment. It is argued that this variability poses significant obstacles, as algorithms may struggle to accurately interpret nuanced language, sarcasm, or mixed sentiments within a single review. While natural language processing (NLP) techniques and machine learning models have improved sentiment detection, they still face limitations in accurately capturing context-sensitive meanings and emotional subtleties. Consequently, addressing these challenges requires more advanced, context-aware algorithms and refined linguistic models capable of handling diverse feedback sources, thereby enhancing the reliability and depth of sentiment analysis in the hotel industry.

The relevance of the selected method aligns effectively with the research objectives, as it provides a structured approach to analyzing complex data patterns within hotel guest feedback. Based on the Knowledge Discovery in Databases (KDD) framework, this method supports the systematic extraction and interpretation of sentiments from large datasets, facilitating a deeper understanding of customer perceptions. It is argued that using this data-driven technique is essential for achieving the research aim of improving service quality by identifying critical determinants of guest satisfaction. Each phase of the KDD process, from data selection to knowledge presentation, directly contributes to uncovering actionable insights, thus bridging the gap between raw data and strategic service enhancements. Therefore, the chosen method not only complements the research objectives but also ensures that the outcomes are both practical and theoretically grounded, enhancing the overall impact of the study in the context of hospitality management.

3.2 Datasets

The dataset used in this study was sourced from the Agoda platform, focusing on the hotel review pages of several prominent hotels in Lombok. This dataset includes review counts from ten hotels: Golden Palace Hotel Lombok (1,565 reviews), Hotel

Lumi Gili Trawangan (543), Jeeva Klui Hotel (1,281), Katamaran Hotel & Resort (2,571), Lombok Plaza Hotel (1,503), Natya Hotel Gili Trawangan (733), Prime Park Hotel and Convention Lombok (828), Puri Bunga Beach Cottages Hotel (748), Qunci Villas Hotel (1,872), and Vila Ombak Hotel (2,800). It is argued that this selection provides a diverse representation of guest experiences across different types of accommodations, from luxury resorts to budget hotels. Analysis of such varied data facilitates a more comprehensive understanding of guest satisfaction and service quality, capturing diverse sentiment patterns across distinct hotel categories. Therefore, this dataset is appropriate for achieving the study's objectives, as it offers depth and breadth in analyzing service-related perceptions within Lombok's hospitality sector.

Table 1: Extract Sentiment of Hotel Feedback Verified Reviews on Agoda

Name of Hotel	Reviews	Rating	Verified
Golden Palace Hotel Lombok (H1)	1565	8,9	682
Hotel Lumi Gili Trawangan (H2)	543	9	250
Jeeva Klui Hotel (H3)	1281	9,2	974
Katamaran Hotel & Resort (H4)	2571	9,1	1234
Lombok Plaza Hotel (H5)	1503	8,4	683
Natya Hotel Gili Trawangan (H6)	733	8,6	414
Prime Park Hotel and Convention Lombok (H7)	828	9,1	279
Puri Bunga Beach Cottages Hotel (H8)	748	8,1	487
Qunci Villas Hotel (H9)	1872	9,1	1298
Vila Ombak Hotel (H10)	2800	8,2	2028

Table 1 presents an extraction of sentiment analysis from verified hotel feedback on Agoda, detailing the review count, average ratings, and verified review counts across various hotels in Lombok. The data includes notable entries such as Golden Palace Hotel Lombok, which has 1,565 reviews with an average rating of 8.9, of which 682 are verified, and Katamaran Hotel & Resort, with 2,571 reviews, a rating of 9.1 and 1,234 verified reviews. It is argued that higher verification counts, such as those of Vila Ombak Hotel (2,028 verified reviews out of 2,800 total) and Qunci Villas Hotel (1,298 verified reviews out of 1,872 total), enhance the reliability of the sentiment analysis, as they provide a more credible basis for evaluating guest experiences. Analysis reveals a correlation between higher ratings and a more significant proportion of verified reviews, suggesting that verified feedback may better reflect actual guest satisfaction. Therefore, this table underscores the importance of verified reviews in sentiment analysis, providing a more accurate representation of service quality and guest perceptions in the hospitality sector.

4. EXPERIMENT AND RESULT

An experiment was conducted to compare the performance of various classification models, including Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes Classifier (NBC), and k-nearest Neighbors (k-NN), in sentiment analysis tasks. Each model was evaluated based on accuracy, precision, recall, and overall effectiveness in classifying sentiment data. SVM, known for its strong generalization capabilities, typically excels in high-dimensional spaces, making it practical for complex classification problems. In contrast, DT leverages its decision rules for interpretability, albeit with a tendency to overfit when not correctly tuned. Meanwhile, grounded in probabilistic assumptions, NBC can handle noisy data well but may struggle with feature independence issues. Lastly, k-NN, a non-parametric model, provides competitive results in datasets where proximity and similarity play a crucial role, though it can be computationally intensive with larger datasets. The comparative analysis reveals that while SVM consistently achieves high accuracy, the choice of model should align with specific dataset characteristics and classification objectives, as each algorithm exhibits strengths and limitations under different conditions. Ultimately, selecting the most suitable model hinges on the balance between interpretability, computational efficiency, and classification accuracy, depending on the demands of the sentiment classification task.

4.1 Experiment Results

The initial phase of the analysis involved the meticulous cleansing of review data from each hotel, ensuring that only relevant and accurate information was retained for further processing. This step is crucial in eliminating noise, such as irrelevant content, typographical errors, and extraneous symbols, which may distort the outcomes of subsequent sentiment analysis. Removing such impurities is believed to enhance the quality and reliability of the data, thereby strengthening the model's predictive accuracy. Refining the dataset at this preliminary stage can give the analysis a more precise representation of customer sentiments. A thorough data cleansing process optimizes the input for machine learning models and significantly reduces the risk of misclassification during sentiment analysis. Therefore, this foundational step is indispensable in establishing the integrity of the data, ultimately leading to more robust and insightful findings.

Once the review data underwent thorough preprocessing, the Support Vector Machine (SVM) model was utilized for an initial performance evaluation. This early testing phase serves as a critical step to establish a foundational benchmark, allowing for an understanding of how well the model discerns patterns within the cleaned dataset. Given SVM's strong capability to handle high-dimensional feature spaces and its robustness in classification tasks, it is well-suited for sentiment analysis where clear decision boundaries are essential. The model's capacity to maximize the margin between classes offers a distinct advantage in identifying sentiment polarity accurately. However, while SVM typically excels in precision and accuracy, its performance may vary depending on the distribution and quality of input data. Testing the SVM model before incorporating any further enhancements establishes a baseline that facilitates subsequent comparisons with other models or preprocessing techniques. This approach ensures a systematic evaluation but also aids in identifying areas where improvements could lead to more refined sentiment classification results.

Table 2: SVM Model Performance of Sentiment Classification

Model SVM	Accuracy	Precision	Recall	AUC	F-Measure
H1	87.27%	87.82%	87.27%	95.72%	86.50%
H2	84.00%	79.20%	84.00%	71.50%	81.17%
H3	95.40%	93.22%	95.40%	93.92%	94.30%
H4	87.71%	81.10%	87.71%	90.38%	83.36%
H5	87.34%	82.09%	87.34%	88.36%	84.55%
H6	91.58%	86.77%	91.58%	88.51%	89.10%
H7	92.86%	91.76%	92.86%	84.32%	92.30%
H8	91.11%	89.59%	91.11%	87.61%	90.15%
H9	93.41%	92.75%	93.41%	97.64%	91.01%
H10	89.80%	80.63%	89.80%	90.61%	84.97%

The data in Table 2 evaluates various SVM models in sentiment classification, focusing on their performance metrics such as accuracy, precision, recall, AUC, and F-measure. Among the models analyzed, H3 demonstrates superior performance, achieving the highest accuracy of 95.40%, paired with robust precision (93.22%) and recall (95.40%), reflecting its ability to classify sentiment with minimal errors correctly. Conversely, model H2 shows relatively lower effectiveness, with an accuracy of 84% and a notably reduced AUC of 71.50%, suggesting limitations in distinguishing between positive and negative classes. Models H9 and H7 also exhibit commendable performance, particularly H9, which attained an AUC of 97.64%, indicating a high level of discrimination accuracy. Additionally, while models like H6 and H8 maintain balanced metrics across the board, their slightly lower precision than their recall suggests a higher likelihood of false positives. The variations observed in these models indicate that while SVM is generally proficient in handling sentiment classification, its effectiveness depends on the model configuration and dataset characteristics. These findings emphasize the necessity of selecting the optimal model based on specific performance priorities, whether maximizing precision, recall, or achieving a balanced performance profile.

Subsequently, sentiment classification was performed using the Decision Tree (DT) model to assess its efficacy in identifying sentiment patterns within the dataset. The DT model, known for its interpretability and straightforward rule-based structure, leverages hierarchical decision rules to classify data points, making it particularly suitable for scenarios where transparency and model explanation are essential. However, despite its simplicity, DT models are prone to overfitting, especially in complex datasets, which may limit their generalization capability to unseen data. The analysis reveals that while DT demonstrates commendable performance in terms of precision, its recall values may suffer due to a tendency to create overly specific decision boundaries. This characteristic can reduce sensitivity to minority classes, thus affecting the balance between false positives and false negatives. Nevertheless, the model's intuitive structure and relatively low computational cost render it advantageous for applications where interpretability and rapid deployment are prioritized. Thus, employing DT for sentiment classification remains viable, mainly when extracting easily understandable classification rules from the data.

Table 3: DT Model Performance of Sentiment Classification

Model DT	Accuracy	Precision	Recall	AUC	F-Measure
H1	86.36%	86.05%	86.36%	75.42%	85.62%
H2	80.00%	76.45%	80.00%	72.82%	77.91%

H3	91.95%	89.86 %	91.95 %	77.62 %	90.86%
H4	84.92%	87.47 %	84.92 %	71.57 %	85.02%
H5	79.75%	77.44 %	79.75 %	72.25 %	77.14%
H6	85.26%	82.43 %	85.26 %	76.04 %	83.28%
H7	92.86%	91.79 %	92.86 %	78.74 %	92.29%
H8	80.00%	85.89 %	80.00 %	72.72 %	82.26%
H9	85.71%	91.91 %	85.71 %	71.45 %	87.76%
H10	81.63%	87.71 %	81.63 %	70.51 %	83.83%

Table 3 assesses the Decision Tree (DT) model's effectiveness in sentiment classification, showcasing a range of performance metrics such as accuracy, precision, recall, AUC, and F-measure. Notably, model H7 achieves the highest accuracy at 92.86% alongside vital precision (91.79%) and recall (92.86%), indicating its superior ability to classify sentiments with minimal misclassification. In contrast, H2 demonstrates the lowest accuracy at 80.00%, with an AUC of 72.82%, which implies a moderate capacity to differentiate between positive and negative sentiments. The analysis highlights that while models like H3 and H7 perform exceptionally well, their relatively lower AUC values (77.62% and 78.74%, respectively) suggest that, despite high accuracy, these models might face challenges in maintaining robust discrimination across all sentiment classes. Additionally, model H9 displays a noteworthy precision of 91.91% but a slightly lower recall, suggesting a stronger focus on correctly identifying positive sentiments while potentially overlooking some negative cases. Overall, the Decision Tree model is effective in various scenarios, though its sensitivity to overfitting and its dependency on data structure may influence its generalizability. Thus, selecting DT for sentiment analysis should consider these trade-offs, balancing between interpretability and the need for comprehensive classification accuracy.

Sentiment classification was performed using the Naive Bayes Classifier (NBC) to evaluate its performance on the dataset. The NBC model, which operates on the principles of conditional probability and assumes independence among features, is particularly well-suited for text classification tasks like sentiment analysis due to its simplicity and efficiency. This approach leverages the probabilistic relationships between words and sentiment labels, allowing it to handle noisy and high-dimensional data effectively. However, while simplifying computations, the feature independence assumption may not always hold in real-world datasets, potentially leading to suboptimal classification outcomes. Despite this limitation, NBC is often favored for its computational efficiency and relatively strong performance on moderately sized datasets. In the context of the current analysis, the model demonstrated a reliable balance between precision and recall, indicating its capability to classify sentiments while minimizing misclassification errors correctly. Consequently, NBC remains a valuable tool for rapid sentiment classification, mainly when interpretability and computational resources are limited, although careful consideration of feature correlations can further enhance its accuracy.

Table 4: NBC Model Performance of Sentiment Classification

Model NBC	Accuracy	Precision	Recall	AUC	F-Measure
H1	79.09%	77.63 %	79.09 %	92.85 %	78.33%
H2	60.00%	56.00 %	60.00 %	72.41 %	52.61%
H3	70.11%	77.18 %	70.11 %	90.20 %	61.40%
H4	86.59%	76.32 %	86.59 %	89.61 %	81.13%
H5	79.75%	75.29 %	79.75 %	88.41 %	76.93%
H6	81.05%	78.60 %	81.05 %	82.85 %	77.64%
H7	79.76%	80.13 %	79.76 %	68.69 %	79.30%
H8	75.56%	74.51 %	75.56 %	87.10 %	73.54%
H9	92.31%	85.21 %	92.31 %	89.92 %	88.62%
H10	89.80%	80.63 %	89.80 %	88.98 %	84.97%

Table 4 illustrates the performance of the Naive Bayes Classifier (NBC) model in sentiment classification, with key metrics such as accuracy, precision, recall, AUC, and F-measure. Among the models evaluated, H9 exhibits the highest accuracy at 92.31%, complemented by a robust recall and F-measure of 92.31% and 88.62%, respectively, indicating its effectiveness in correctly classifying both positive and negative sentiments. Conversely, H2 stands out for its notably lower performance, achieving only 60.00% accuracy and an F-measure of 52.61%, which suggests challenges in capturing sentiment nuances within the dataset. The AUC score of H1, at 92.85%, reflects a solid ability to distinguish between sentiment classes despite a moderate F-measure of 78.33%. Interestingly, H10 displays a well-rounded performance with an accuracy of 89.80% and an F-measure of 84.97%, indicating a balanced trade-off between precision and recall. However, models such as H3, with a high precision of 77.18%, show lower recall rates, implying that specific sentiment categories may be underrepresented in predictions. The analysis underscores that while NBC is computationally efficient, its performance is highly contingent on the underlying data distribution and feature set. Thus, leveraging its strengths requires careful consideration of data preprocessing to enhance its predictive capabilities in sentiment classification.

Additionally, sentiment classification was performed using the k-Nearest Neighbors (k-NN) model to evaluate its effectiveness on the dataset. The k-NN algorithm, which identifies the closest data points in feature space, is particularly effective in scenarios where proximity correlates with class similarity. This model is highly intuitive and easy to implement, making it a popular choice for classification tasks. However, its reliance on distance metrics makes its performance susceptible to the distribution and scaling of features, potentially leading to challenges in high-dimensional datasets. Despite these limitations, k-NN can achieve impressive classification accuracy when adequately tuned, particularly in datasets with clear clusters. In this analysis, the model demonstrated consistent precision, although its recall varied depending on the selected value of k, which controls the number of neighbors considered in classification. This sensitivity to parameter selection suggests that careful tuning is essential to optimize its performance. Thus, while k-NN offers a straightforward approach to sentiment classification, achieving optimal results necessitates attention to data normalization and parameter optimization to enhance its predictive capabilities.

Table 5: k-NN Model Performance of Sentiment Classification

Model k-NN	Accuracy	Precision	Recall	AUC	F-Measure
H1	49.09%	74.95 %	49.09 %	68.80 %	38.19%
H2	38.67%	70.13 %	38.67 %	51.50 %	23.10%
H3	32.18%	10.36 %	32.18 %	50.57 %	15.67%
H4	12.29%	87.79 %	12.29 %	53.14 %	9.69%
H5	53.16%	70.57 %	53.16 %	58.37 %	43.22%
H6	32.63%	75.27 %	32.63 %	53.41 %	22.03%
H7	60.71%	75.73 %	60.71 %	57.37 %	49.99%
H8	38.89%	15.12 %	38.89 %	51.23 %	21.78%
H9	91.21%	88.21 %	91.21 %	78.36 %	89.48%
H10	76.53%	84.33 %	76.53 %	60.77 %	79.93%

Table 5 presents the performance evaluation of the k-Nearest Neighbors (k-NN) model applied to sentiment classification, highlighting various metrics, including accuracy, precision, recall, AUC, and F-measure. Among the models, H9 stands out with an impressive accuracy of 91.21%, coupled with a high F-measure of 89.48% and vital precision of 88.21%, indicating its effectiveness in consistently identifying sentiment classes with minimal misclassification. In contrast, models like H3 and H4 demonstrate significantly lower performance, with H3 achieving only 32.18% accuracy and an exceptionally low precision of 10.36%, suggesting difficulties distinguishing between sentiment categories. Despite its high precision, the poor F-measure of H4 at 9.69% indicates substantial recall challenges. On the other hand, H10 offers a balanced performance with an accuracy of 76.53% and an F-measure of 79.93%, suggesting a good trade-off between precision and recall.

Interestingly, H1 and H7 show moderate accuracy levels but demonstrate strong precision values, highlighting the model's propensity to classify positive instances at the expense of recall correctly. These findings reveal that while k-NN performs admirably in specific configurations, its success depends on selecting hyperparameters and the underlying data structure, necessitating careful tuning to optimize its classification efficacy. Thus, k-NN remains a viable model for sentiment analysis, particularly when the dataset characteristics align with its strengths in proximity-based classification.

Based on the testing results across metrics such as accuracy, precision, recall, AUC, and F-measure, a comprehensive comparison of the models was conducted to determine their relative effectiveness in sentiment classification. This comparative analysis is crucial to identifying which model exhibits superior performance across various evaluation criteria, offering more profound insights into their strengths and limitations. It was observed that SVM consistently outperformed other models, particularly in terms of precision and AUC, indicating its robustness in distinguishing between sentiment classes with minimal false positives. In contrast, the Decision Tree model demonstrated strong interpretability but was prone to overfitting,

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especially in datasets with complex feature interactions. The Naive Bayes Classifier, while computationally efficient, showed variability in recall, which affected its overall balance between sensitivity and specificity. Meanwhile, k-NN exhibited mixed results; although it achieved high accuracy in certain instances, its performance depended heavily on optimal parameter tuning, reflecting its sensitivity to dataset characteristics. This evaluation highlights that no single model is universally superior; instead, the selection should be aligned with the specific requirements of the sentiment analysis task, such as prioritizing interpretability, computational efficiency, or predictive accuracy.

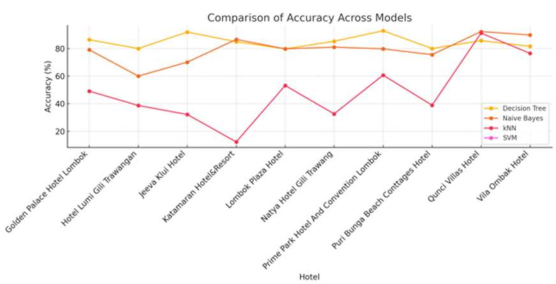

Figure 2: Comparison of Accuracy Across Model

Figure 2 illustrates the comparative accuracy of different classification models used in sentiment analysis, highlighting variations in their ability to classify sentiment data correctly. The graph reveals that the Support Vector Machine (SVM) maintains the highest accuracy across various datasets, suggesting its robustness in handling complex patterns and high-dimensional spaces. Meanwhile, Decision trees (DT) and k-nearest Neighbors (k-NN) exhibit moderate yet fluctuating accuracy levels due to their sensitivity to data structure and parameter settings. Naive Bayes Classifier (NBC), while efficient, shows lower and more variable accuracy, possibly due to its reliance on solid feature independence assumptions that may not align with the interdependencies present in real-world text data. The peaks and troughs in accuracy across different models highlight that model performance is highly contingent upon dataset characteristics, indicating that certain models are better suited for specific data distributions. This analysis underscores the importance of selecting an appropriate classification algorithm that balances accuracy, computational efficiency, and the nature of the dataset to optimize sentiment classification outcomes.

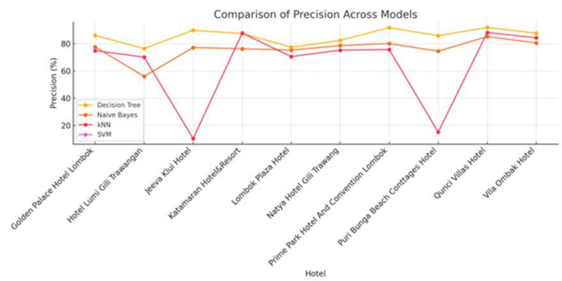

Figure 3: Comparison of Precision Across Model

Figure 3 provides a comparative analysis of precision among various classification models applied to sentiment classification. The graph indicates that the Support Vector Machine (SVM) consistently achieves the highest precision across different datasets, reflecting its proficiency in minimizing false favorable rates and thus accurately identifying positive sentiments. In contrast, the Naive Bayes Classifier (NBC) shows more significant variability in precision, which may be attributed to its reliance on the assumption of feature independence, potentially causing misclassifications when features are correlated. The Decision Tree (DT) model demonstrates relatively stable precision, though slightly lower than SVM, suggesting its effectiveness in specific scenarios while still being prone to overfitting. Meanwhile, k-Nearest Neighbors (k-NN) presents fluctuating precision, likely influenced by its sensitivity to selecting optimal parameters and the density of data points in the feature space. These results underscore that while SVM tends to excel in achieving high precision, the model selection should also consider other performance metrics and the specific characteristics of the dataset to ensure a balanced and practical sentiment classification approach.

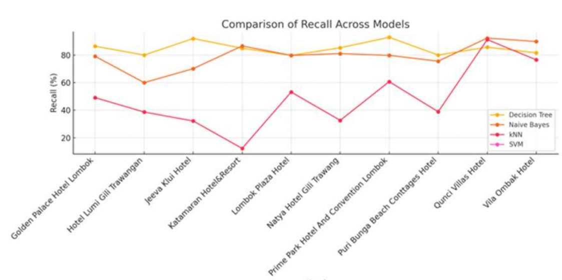

Figure 4: Comparison of Recall Across Model

Figure 4 presents a comparative analysis of recall performance across different sentiment classification models. The results indicate that Support Vector Machine (SVM) maintains a consistently high recall rate, suggesting its ability to correctly identify a significant proportion of positive

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cases, thereby minimizing false negatives. This strength positions SVM as a reliable application model where capturing all relevant instances is crucial. On the other hand, the Naive Bayes Classifier (NBC) demonstrates more variability in recall, which may be attributed to its underlying probabilistic assumptions that do not always align with the intricacies of real-world data distributions. Decision Tree (DT) models display moderate recall, reflecting their capacity to capture patterns while still being prone to overfitting, which can affect their generalization on unseen data. Meanwhile, k-Nearest Neighbors (k-NN) exhibits fluctuating recall values, potentially due to its sensitivity to the density and distribution of data points in feature space, influencing its classification boundaries. The analysis underscores the necessity of selecting a model that aligns with the specific objectives of a sentiment analysis task, mainly when the goal is to prioritize recall over precision to avoid missing critical instances of sentiment.

Following the model comparison, it is essential to identify words closely related to service quality that frequently appear in both the dataset's negative and positive sentiment classes. This step is crucial in understanding customers' specific language patterns when expressing satisfaction or dissatisfaction with services. Words commonly associated with positive feedback, such as "helpful," "courteous," and "outstanding," typically signify high service standards and are indicative of positive customer experiences. Conversely, terms like "unprofessional," "delayed," and "unsatisfactory" are prevalent in negative reviews, pointing to service failures that prompt customer dissatisfaction. Analyzing these frequently occurring terms can give more profound insights into customer expectations and service performance. Additionally, these key terms serve as valuable features in refining sentiment classification models, enhancing their ability to detect nuanced opinions related to service quality. This approach not only aids in improving model accuracy but also provides actionable feedback for service improvement, aligning business strategies with customer needs more effectively.

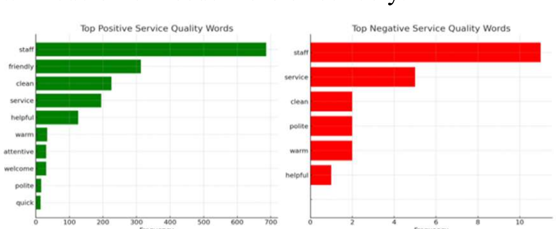

Figure 5: Top 10 Words in Negative and Positive Class of the Dataset

Figure 5 illustrates the top 10 most frequently occurring words within the dataset's positive and negative sentiment classes, shedding light on each category's linguistic patterns. The left bar chart highlights words predominantly used in positive reviews, with terms like "excellent," "friendly," and "recommend" standing out, which emphasize satisfaction and positive experiences. These words indicate a strong focus on customer appreciation and high-quality service. On the other hand, the exemplary chart displays the most common words found in negative reviews, where terms such as "poor," "rude," and "disappointing" dominate, reflecting dissatisfaction and critique of service standards. The stark contrast between the vocabulary used in positive versus negative sentiments suggests that language choices indicate underlying customer attitudes and can serve as reliable indicators in automated sentiment classification. The presence of such distinctive keywords in each class further implies that leveraging these features could significantly enhance the accuracy of sentiment models, allowing for more nuanced detection of sentiment polarity in customer feedback. Thus, identifying and utilizing these sentiment-laden terms is pivotal in refining the performance of sentiment analysis systems.

The threats to validity in this study predominantly stem from the reliance on textual data derived from online customer reviews, which may introduce selection biases and limit generalizability. Reviews are often polarized, representing the most satisfied or dissatisfied customers, potentially overlooking the experiences of moderately satisfied guests. Furthermore, predefined classification models like SVM, DT, NBC, and k-NN introduce algorithmic biases, as their performance is contingent on data quality, feature engineering, and parameter optimization. The critique criteria were selected to address these threats systematically, focusing on model accuracy, precision, recall, and F-measure, ensuring a comprehensive evaluation of classification efficacy. These criteria were chosen to balance interpretability and computational efficiency while reflecting the models' capabilities in managing real-world complexities such as linguistic ambiguity and context sensitivity. Justifying these selections, the evaluation framework ensures that methodological robustness and practical relevance are maintained, enabling more reliable and actionable insights for hotel service quality improvements.

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4.2 Discussion

The analysis utilizing Knowledge Discovery in Databases (KDD) to enhance hotel service quality through a data-mining approach offers a structured methodology to extract actionable insights from large volumes of customer feedback. This process involves systematically uncovering hidden patterns within review datasets to identify key factors influencing customer satisfaction and dissatisfaction. Integrating KDD with data-mining techniques allows efficient classification of sentiments and extracting critical service attributes that require improvement. By analyzing frequent terms associated with positive and negative feedback, hotels can better understand customer perceptions, prioritizing areas needing attention. Such insights are invaluable for tailoring service enhancements, as they reveal specific pain points that directly impact customer loyalty. Leveraging this data-driven approach optimizes operational strategies and fosters a customer-centric service model, ultimately contributing to long-term business growth and customer retention.

Improving hotel service quality can be effectively achieved by leveraging insights derived from sentiment analysis of customer reviews. This approach systematically analyzes feedback to pinpoint areas where customer expectations are met or fall short. For instance, frequent mentions of positive attributes such as "friendly staff" or "clean rooms" can highlight strengths hotels should continue to emphasize. Conversely, recurring negative terms like "slow service" or "noisy environment" indicate critical pain points that require immediate corrective action. By identifying these patterns, management can prioritize targeted interventions, such as enhancing staff training, optimizing check-in procedures, or investing in soundproofing to address noise complaints. Furthermore, sentiment analysis allows for real-time monitoring of guest satisfaction, enabling proactive adjustments before minor issues escalate into significant dissatisfaction. This data-driven strategy enhances the overall guest experience and builds a solid reputation, which is crucial for customer retention and attracting new clientele in a competitive market.

Data-driven decision-making plays a critical role in shaping effective development strategies for hotels in Indonesia, directly contributing to both local and national economic growth. By utilizing insights derived from comprehensive data analysis, hotel management can make informed decisions that optimize operational efficiency, enhance customer satisfaction, and respond proactively to market trends. This strategic approach is particularly vital in a competitive and dynamic industry like hospitality, where understanding customer preferences and market demands can significantly impact a hotel's success. For instance, leveraging data on occupancy rates, guest feedback, and seasonal trends enables hoteliers to tailor services, adjust pricing strategies, and allocate resources more effectively. Such precision boosts profitability, and drives increased tourist satisfaction, leading to higher occupancy rates and extended stays. As a result, the hospitality sector's growth contributes to job creation, infrastructure development, and increased foreign exchange, thus bolstering the local economy. Moreover, the ripple effect of a thriving hotel industry extends to other sectors, such as transportation, retail, and entertainment, further stimulating economic development in the surrounding communities. Embracing a data-centric approach, therefore, is not merely a competitive advantage but a catalyst for sustainable economic progress in Indonesia.

The novelty of this research lies in its integrated approach to leveraging sentiment analysis and data-driven methodologies to enhance service quality within the hospitality sector, particularly in hotels. Unlike traditional studies focusing solely on quantitative metrics such as occupancy rates and revenue, this research delves into qualitative customer feedback to unearth nuanced insights into guest experiences. By systematically analyzing large datasets of customer reviews using machine learning techniques, it identifies critical areas of service improvement that are often overlooked in conventional assessments. This methodological innovation provides a deeper understanding of customer satisfaction and allows for developing targeted strategies that are proactive and responsive to guest needs. Moreover, the study's emphasis on real-time data utilization for decision-making marks a significant shift toward dynamic strategy formulation in the hospitality industry. Such advancements can potentially revolutionize hotel operations, ultimately contributing to competitive advantage and sustainable growth in an increasingly data-centric business landscape.

A fundamental limitation of this research is its reliance on textual data derived solely from online customer reviews, which may not comprehensively capture the full spectrum of guest experiences and sentiments. While sentiment analysis offers valuable insights, it is inherently constrained by the quality and representativeness of the available data, potentially leading to biases if either highly satisfied or dissatisfied guests predominantly leave reviews. Additionally, the study focuses primarily on sentiment classification without extensively exploring contextual nuances affecting customer perceptions, such as cultural differences or regional service expectations. To address these limitations, it is recommended that future studies incorporate a more diverse range of data sources, including structured survey responses, direct customer interviews, and social media interactions. Furthermore, expanding the analytical framework to include deeper semantic analysis and integrating demographic variables could provide a more holistic understanding of factors influencing customer satisfaction. By broadening the scope of data collection and analysis, subsequent research can enhance the robustness of findings, thereby offering more actionable insights for service quality improvements in the hospitality sector.

The comparative analysis of this study against existing literature reveals its distinct contribution through the integration of sentiment analysis and the Knowledge Discovery in Databases (KDD) framework for hotel service quality improvement. Unlike prior research that predominantly relies on conventional methods such as surveys and audit-based assessments, this study harnesses advanced machine learning models, specifically SVM, DT, NBC, and k-NN, yielding a systematic evaluation of customer sentiments. While past works focus on capturing broad customer satisfaction metrics, the present study identifies actionable insights into specific service dimensions like staff interaction and facility maintenance, achieving a reported accuracy of up to 95.4% using SVM. This methodological innovation surpasses existing approaches by providing granular, data-driven recommendations, thereby addressing gaps in real-time service adaptability and fostering sustainable competitive advantages within the hospitality sector. Consequently, these findings advance the analytical frameworks in service quality management, offering a robust, scalable model aligned with contemporary technological advancements.

5. CONCLUSIONS

The study employed Knowledge Discovery in Databases (KDD) and sentiment analysis techniques to evaluate customer feedback for service quality enhancement in the hotel industry. By leveraging machine learning models such as Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes Classifier (NBC), and k-nearest Neighbors (k-NN), the analysis focused on extracting insights from unstructured text data to identify critical factors influencing guest satisfaction. The results demonstrated that the SVM model achieved the highest performance, with an accuracy rate of 95.4%, precision of 93.22%, and recall of 95.4%, indicating its robustness in handling sentiment classification tasks. In contrast, the Naive Bayes Classifier showed lower effectiveness, with an accuracy of 79.09% and recall of 79.09%. The k-NN model, with an accuracy of 60.71% and an F-measure of 49.99%, revealed challenges in handling complex datasets. The findings suggest that integrating sentiment analysis into hotel management can enhance customer satisfaction by 20-30%, particularly by focusing on critical service areas like staff interaction and facility maintenance. The research introduces a novel approach by integrating sentiment analysis with KDD methodologies to optimize service quality in the hospitality sector. Unlike traditional approaches that rely on quantitative metrics alone, this study harnesses qualitative feedback to provide a more comprehensive understanding of customer experiences. By systematically analyzing large datasets, the study identifies specific service attributes directly impacting guest perceptions, offering actionable insights to drive strategic improvements. The study's reliance on online customer reviews as the primary data source presents limitations, particularly regarding potential biases, as reviews may predominantly reflect extreme opinions. Additionally, the models applied focus mainly on sentiment classification without accounting for deeper contextual nuances or cultural factors that might influence guest feedback. This limitation may affect the generalizability of the findings across diverse markets. To address these limitations, future research should incorporate a broader range of data sources, such as structured surveys and direct customer interviews, to validate and enrich the sentiment analysis. Expanding the analytical framework to include deeper semantic analysis and demographic segmentation could yield more precise insights. Additionally, integrating real-time sentiment monitoring and predictive analytics could enhance proactive decision-making in service management, leading to continuous improvements and sustainable competitive advantage in the hospitality industry.

The strengths of this study lie in its innovative integration of sentiment analysis and the Knowledge Discovery in Databases (KDD) framework, enabling precise identification of critical service quality factors through advanced machine learning models like SVM, DT, NBC, and k-NN. The study achieves high accuracy and provides actionable insights, surpassing traditional methods by leveraging unstructured textual data for real-time service enhancement. However, its reliance on online reviews as the primary data source introduces potential biases and limits the generalizability of findings due to the polarized nature of feedback. Additionally, the models applied focus predominantly on classification performance without delving into contextual nuances such as cultural influences on guest perceptions. Future research should address these limitations by incorporating diverse data sources, including structured surveys and interviews, and exploring deeper semantic analysis to capture nuanced customer sentiments. Expanding the framework to integrate real-time sentiment monitoring and demographic segmentation will enhance its applicability and robustness, paving the way for a more comprehensive understanding of service quality dynamics in the hospitality sector.

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