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A Hybrid CNN-LSTM Model with SMOTE for Enhanced Sentiment Analysis of Hotel Reviews

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Abstract−The growing reliance on online reviews as a critical decision-making tool in the hospitality industry underscores the need for robust sentiment analysis methodologies. Understanding customer feedback is essential for hotels to enhance service quality and maintain a competitive edge in an increasingly digital marketplace. However, traditional sentiment analysis models often encounter difficulties processing unstructured textual data, particularly when faced with class imbalances where positive reviews dominate, overshadowing critical negative feedback. To address these challenges, this study investigates integrating a hybrid Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) model with the Synthetic Minority Over-sampling Technique (SMOTE) to improve sentiment classification accuracy. Utilizing a dataset of 665 reviews from THE 1O1 Bandung Dago Hotel, the model leverages CNN's capability to capture local features and LSTM's strength in handling sequential dependencies, resulting in a more nuanced analysis of customer sentiments. The application of SMOTE effectively balances the dataset, addressing the class imbalance issue, which often skews sentiment classification. This approach improves predictive accuracy and provides actionable insights to enhance customer satisfaction strategies. The study achieved an overall classification accuracy of 77%, with precision at 78%, recall at 77%, an F1 score of 77.5%, and an AUC score of 0.81, reflecting discriminatory solid capability. Future research could focus on model optimization, multilingual sentiment analysis, aspect-based sentiment insights, and real-time sentiment monitoring to further refine customer feedback analysis and support strategic decision-making in the hospitality sector.

Keywords: CNN; LSTM; SMOTE; Sentiment Classification; Hotel

1. INTRODUCTION

Sentiment analysis of hotel reviews plays a crucial role in the hospitality industry, offering insights into customer experiences and informing business strategies. However, the challenge of processing unstructured textual data, especially when faced with class imbalances, complicates the classification task, often resulting in biased predictions. To address this, leveraging a hybrid deep learning architecture that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks presents a robust solution [1], [2]. CNN excels at capturing local features within the text, while LSTM effectively handles sequential dependencies, enhancing the overall classification accuracy. Meanwhile, the Synthetic Minority Over-sampling Technique (SMOTE) addresses the class imbalance issue by generating synthetic samples, thereby improving the model's generalization capability [3], [4]. This integrated approach refines sentiment classification and reduces overfitting, ensuring more reliable analysis outcomes. Employing this methodology is particularly advantageous in the context of hotel reviews, where accurate sentiment detection is essential for maintaining competitive customer satisfaction metrics. A hybrid CNN-LSTM model, enhanced with SMOTE, ultimately represents a significant advancement in the field, offering a scalable solution to the complex sentiment analysis problem in highly dynamic datasets.

The growing reliance on online reviews as a critical decision-making tool for potential customers underscores the urgency of enhancing sentiment analysis methodologies. Understanding customer feedback is essential for maintaining service quality and gaining a competitive edge in the hospitality sector [5]–[9]. However, traditional sentiment classification models often struggle with the nuanced language used in reviews. They are further impeded by class imbalance issues, where many positive reviews may overshadow negative feedback. This inadequacy necessitates a more sophisticated approach that improves classification accuracy and addresses data imbalances to prevent biased insights. Integrating deep learning models such as CNN-LSTM with techniques like SMOTE mitigates these challenges, offering a more reliable analysis framework [10]–[13]. By refining how sentiment data is interpreted, this research contributes to actionable intelligence that empowers businesses to respond more effectively to customer needs. As such, advancing these techniques holds substantial implications for optimizing customer satisfaction and retention in an increasingly digital marketplace.

This research aims to develop an advanced sentiment classification model that effectively addresses the limitations of analyzing unstructured textual data, particularly in the context of hotel reviews. By leveraging a hybrid CNN-LSTM architecture integrated with the SMOTE technique, the study seeks to overcome feature extraction and class imbalance challenges [14]–[16]. These challenges often lead to reduced predictive accuracy and unreliable sentiment interpretation, which, in turn, hampers strategic decision-making within the hospitality industry. A combined deep learning approach allows for capturing spatial patterns in text and long-term dependencies, enhancing the model's ability to interpret complex sentiment expressions. Additionally, applying SMOTE is anticipated to improve the balance of training data, leading to a more robust and generalizable classification model [17]–[19]. This

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research, therefore, aims to contribute to more precise sentiment analysis, enabling businesses to derive actionable insights from customer feedback and ultimately enhance service quality and customer satisfaction.

This research leverages a dataset comprising 665 hotel reviews sourced from the Agoda platform, specifically focusing on customer feedback for The 101 Bandung Dago Hotel. The analysis aims to assess the efficacy of a hybrid CNN-LSTM model combined with the SMOTE technique in accurately classifying sentiment within these reviews. By utilizing real-world data, the study ensures the model's applicability to actual user experiences, enhancing its findings' relevance to the hospitality sector. The choice of CNN-LSTM architecture allows for the effective extraction of spatial features and temporal patterns. At the same time, the application of SMOTE addresses the issue of class imbalance, which often skews sentiment analysis results. This methodology is expected to enhance sentiment classification accuracy and provide deeper insights into customer satisfaction dynamics, enabling more effective data-driven strategies for service improvement. Such an approach demonstrates the potential for practical implementation in refining customer feedback systems, ultimately improving service quality and customer retention.

This research offers theoretical contributions and practical implications that are pivotal in advancing the field of sentiment analysis within the hospitality domain. Theoretically, integrating a hybrid CNN-LSTM model with the SMOTE technique enriches the existing literature by addressing the limitations of traditional machine learning models in handling unbalanced datasets and extracting intricate patterns from textual data [20]–[22]. This innovative framework enhances the understanding of how deep learning models can be optimized for text classification tasks, thereby setting a foundation upon which future studies can build. Regarding practical implications, the model developed in this study holds significant potential for businesses, particularly in the hospitality industry, where customer feedback is critical in shaping service strategies [23]–[27]. Organizations are better equipped to extract actionable insights by providing a more accurate sentiment classification, allowing for a more nuanced understanding of customer satisfaction trends. Ultimately, this dual contribution bridges existing knowledge gaps and facilitates a data-driven approach to decision-making, essential for maintaining competitiveness in a rapidly evolving digital landscape.

Several studies have explored the use of machine learning and deep learning models for sentiment analysis, mainly focusing on the classification of customer reviews. Among these, hybrid models combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have demonstrated promising results in capturing spatial features and sequential dependencies within text data [28]–[32]. Such models have been applied in diverse fields, yet there remains a persistent challenge related to data imbalance, where minority classes, often critical in sentiment contexts, are underrepresented. Some studies have employed resampling techniques like SMOTE to mitigate this, effectively enhancing model performance [33]. However, few investigations have fully integrated hybrid deep learning models with robust oversampling strategies, especially in analyzing sentiment in hospitality reviews. This gap suggests a need for a more comprehensive approach that combines CNN-LSTM architectures and systematically addresses class imbalance to optimize classification accuracy. Thus, while prior research provides a foundation, further advancements are necessary to refine these methodologies for domain-specific applications, ensuring theoretical and practical improvements in sentiment classification.

2. RESEARCH METHODOLOGY

2.1 Implementation of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) Architectures

Implementing Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) architectures offers a powerful approach to processing and analyzing sequential text data for sentiment classification tasks. CNN is adept at identifying local patterns and features within text sequences, leveraging its convolutional layers to capture n-gram-level information efficiently [34], [35]. In contrast, LSTM excels in capturing long-range dependencies and contextual information, making it particularly suitable for handling complex sentence structures and retaining important contextual cues over extended text sequences [30], [31]. The integration of these two architectures forms a synergistic model that capitalizes on the strengths of both CNN's feature extraction capabilities and LSTM's sequential learning proficiency. Such a hybrid model improves classification accuracy and addresses the inherent challenges of natural language processing, particularly in domains where sentiment nuances are critical. This dual architecture thus enhances the robustness of sentiment analysis, paving the way for more refined and actionable insights in various applications, including customer feedback systems and market sentiment analysis.

The experiment leverages Google Colab as the primary development environment, utilizing Python for efficient implementation and computational processing. Various specialized libraries are employed to streamline the workflow and enhance the functionality of the sentiment analysis model. Pandas and NumPy facilitate data manipulation and numerical computations, while Google Drive integration ensures seamless access to datasets. TensorFlow, combined with Keras modules, provides a robust framework for building the hybrid CNN-LSTM model, utilizing layers such as Embedding, Conv1D, MaxPooling1D, LSTM, Dense, and Dropout for effective feature extraction and sequence learning. Preprocessing steps involve tokenization and padding to standardize text input, while LabelEncoder assists in converting categorical labels into a numerical format. For model evaluation, the suite of metrics includes a confusion matrix, classification report, ROC curve, and various performance scores such as

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accuracy, precision, recall, and F1. Additionally, integrating SMOTE addresses data imbalance issues, thereby improving classification robustness. Visualization tools like Matplotlib and Seaborn are employed to generate insightful graphical representations of data distributions and model performance. This comprehensive setup ensures efficient handling of large datasets and optimizes the model's predictive accuracy, ultimately contributing to more reliable sentiment analysis outcomes.

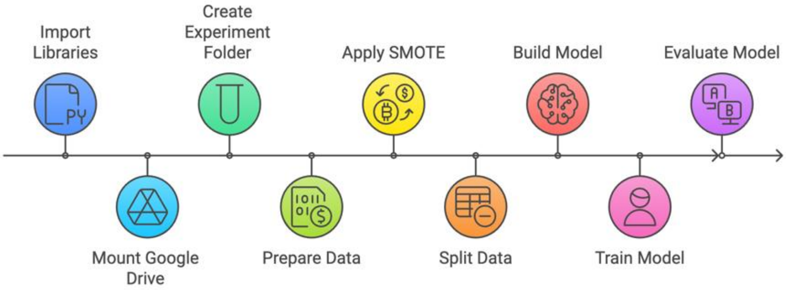

Figure 1. Sentiment Analysis Experiment Using A hybrid CNN-LSTM Model Combined with SMOTE

Figure 1 illustrates a structured workflow to implement a sentiment analysis experiment using a hybrid CNN-LSTM model combined with SMOTE. The process begins with importing necessary libraries and creating a dedicated experiment folder to organize outputs systematically. The dataset is mounted and accessed from Google Drive, ensuring seamless data integration. Once the data is prepared and preprocessed, SMOTE is applied to balance the dataset, thereby addressing potential class imbalances that could skew model predictions. Subsequently, the dataset is divided into training and testing sets, enabling robust model evaluation. The architecture is then constructed by leveraging the combined strengths of CNN for feature extraction and LSTM for capturing sequential dependencies. Once the model is built, training is performed to optimize the parameters, followed by a comprehensive evaluation to assess its accurate classification of sentiments. This workflow ensures a systematic approach to optimizing the model's accuracy and generalizability to real-world datasets, thus enhancing the reliability of sentiment classification outcomes.

To address the data imbalance inherent in sentiment classification, the Synthetic Minority Over-sampling Technique (SMOTE) generates synthetic samples for underrepresented classes, ensuring a more balanced dataset. This approach is particularly effective in enhancing the predictive accuracy of machine learning models, as it reduces the risk of bias towards the majority class. The dataset is subsequently partitioned, with 80% allocated for training and 20% reserved for testing, allowing for a rigorous evaluation of the model's performance. This distribution strikes an optimal balance between having sufficient data for training and retaining a meaningful portion for validation. By enriching the minority class representation and employing a structured data split, the experiment improves model generalization and enhances the reliability of sentiment predictions. Such a methodological approach is essential for extracting more accurate insights from customer reviews, supporting more informed decision-making processes.

2.2 The 101 Bandung Dago Hotel

THE 1O1 Bandung Dago Hotel, a prominent four-star establishment, offers an exceptional blend of modern amenities and strategic location, catering primarily to solo travelers seeking both comfort and convenience. Situated in the vibrant Dago area, this hotel provides easy access to Bandung's key attractions, such as Cihampelas Walk and Gedung Sate, making it an ideal base for exploring the city's cultural and shopping destinations. The hotel's facilities are thoughtfully designed to enhance guest experiences, featuring amenities like the Dutch Blue Pool for leisurely swims and Whales Spa & Massage for relaxation. Accommodations are stylishly appointed, with rooms equipped with air conditioning, complimentary Wi-Fi, and refreshing shower facilities. In contrast, select rooms offer panoramic city views that add to the allure of the stay. An indoor pool and a chic restaurant further elevate the guest experience, ensuring a relaxing yet luxurious ambiance. The surrounding area, known for its trendy cafes and scenic mountain vistas, enriches the overall stay, appealing particularly to those who value both modern comfort and urban exploration. This combination of premium facilities, convenient location, and attentive service positions THE 1O1 Bandung Dago Hotel as a distinguished choice for discerning solo travelers.

Figure 2. Hotel Facilities (Source: Agoda)

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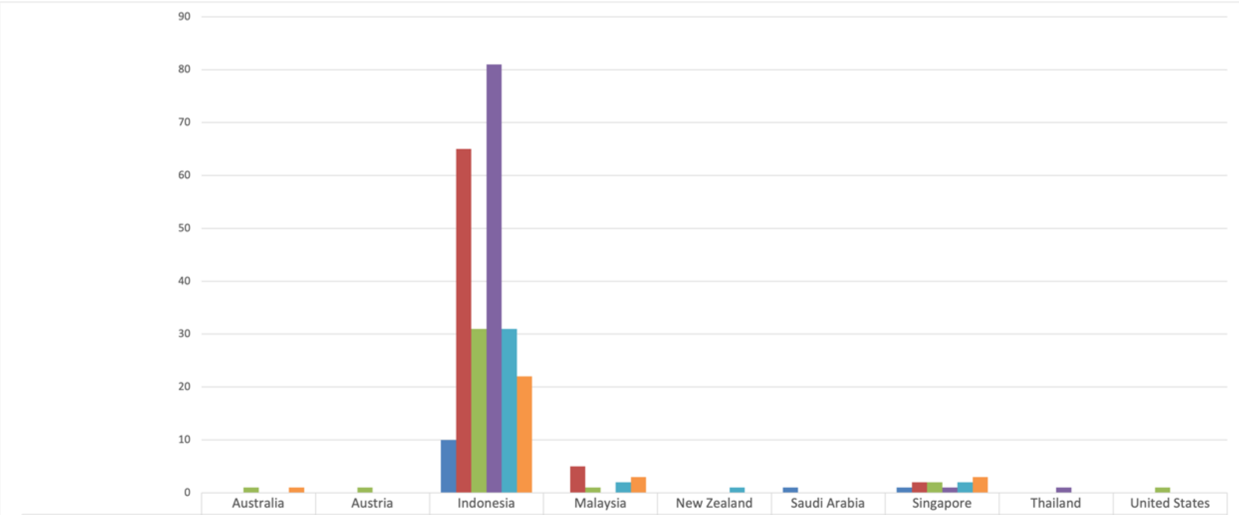
Figure 2 presents an overview of the diverse facilities available at THE 1O1 Bandung Dago Hotel, highlighting the establishment's commitment to providing a comfortable and modern experience for its guests. The images showcase various amenities, including a stylish indoor pool that offers a relaxing environment amidst a chic, urban setting. Additionally, the hotel features open-air dining spaces that blend natural elements with contemporary aesthetics, catering to travelers seeking comfort and a connection to the outdoors. The architectural design, emphasizing transparency and light, reflects a thoughtful approach to enhancing the overall guest experience. These facilities elevate the aesthetic appeal and foster a sense of tranquility and exclusivity. Integrating such well-appointed amenities makes the hotel an attractive option for those looking to balance relaxation with the convenience of a central location in Bandung. This blend of modern design and functional spaces underscores the hotel's dedication to providing a refined stay for its clientele.

The analysis of guest types based on the dataset of 269 accounts, categorized by country of origin, serves as a crucial foundation for market segmentation, enabling hotels to refine their marketing strategies and tailor services more effectively. By identifying the predominant segments, such as families with young children and couples from the domestic Indonesian market, targeted promotional efforts can be designed to enhance customer engagement within this demographic. Additionally, the presence of international guests, though less substantial, highlights the potential for expanding outreach to travelers from neighboring countries like Malaysia and Singapore, particularly those seeking business and solo travel experiences. This segmentation is instrumental in optimizing product offerings and aligning services with the expectations of diverse customer groups. By leveraging these insights, hotels are better positioned to implement strategic marketing campaigns, enhance customer satisfaction, and improve occupancy rates. Thus, understanding the distribution of guest types informs marketing initiatives and supports the sustainable growth of the hotel's market share in a competitive industry.



	Australia	Austria	Indonesia	Malaysia	New Zealand	Saudi Arabia	Singapore	Thailand	United States
Business traveler			10			1	1		
Couple			65	5			2		
Family with teens	1	1	31	1			2		1
Family with young children			81				1	1	
Group			31	2	1		2		
Solo traveler	1		22	3			3		

Figure 3. Guest Type based on Country of Origin (269 Accounts)

Figure 3 provides a visual representation of the distribution of guest types based on their country of origin, encompassing data from 269 accounts. The chart reveals that most visitors are from Indonesia, with an exceptionally high proportion of families traveling with young children and couples, suggesting that the hotel appeals strongly to domestic leisure travelers. In contrast, guests from other countries such as Australia, Malaysia, and Singapore exhibit a more diverse mix of guest profiles, including business travelers and solo visitors, albeit in significantly smaller numbers. This distribution indicates a predominant reliance on the local market while attracting a modest international clientele, likely due to the hotel's strategic location and family-friendly amenities. The concentration of Indonesian guests can be attributed to the convenience and affordability of local tourists. In contrast, the presence of international guests suggests that the hotel's facilities and services meet diverse needs, from business trips to family vacations. Overall, these insights highlight the hotel's ability to cater to both domestic and select international segments, positioning it well within the competitive landscape of Bandung's hospitality sector.

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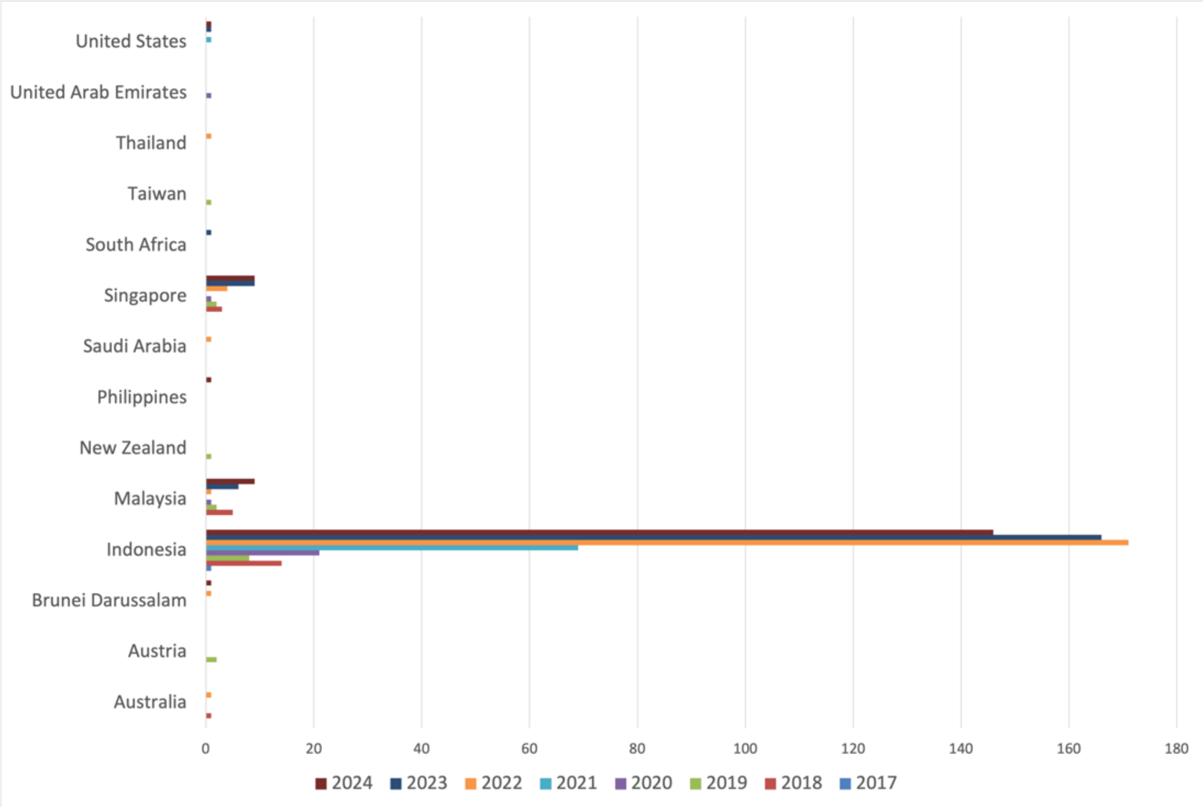

Figure 4. Hotel Guest Trends based on Year of Visit (664 Accounts)

Figure 4 illustrates the distribution of hotel guests over the years, categorized by their country of origin, based on data from 664 accounts. The graph reveals a significant concentration of visits from Indonesian guests across all recorded years, indicating solid and consistent domestic patronage. In contrast, the number of international visitors from countries such as Malaysia, Singapore, and Australia, although present, remains comparatively modest, reflecting either targeted marketing or geographical proximity. The trends suggest a stable preference among local travelers for the hotel, which may be attributed to its convenient location, competitive pricing, and familiarity among Indonesian customers. Meanwhile, the sporadic yet consistent international visits hint at potential areas for growth in attracting overseas tourists, mainly from Southeast Asian neighbors. This temporal analysis is crucial for understanding fluctuations in guest demographics over time. It can inform strategies to boost occupancy during periods of lower international engagement, optimizing revenue streams and sustaining market competitiveness.

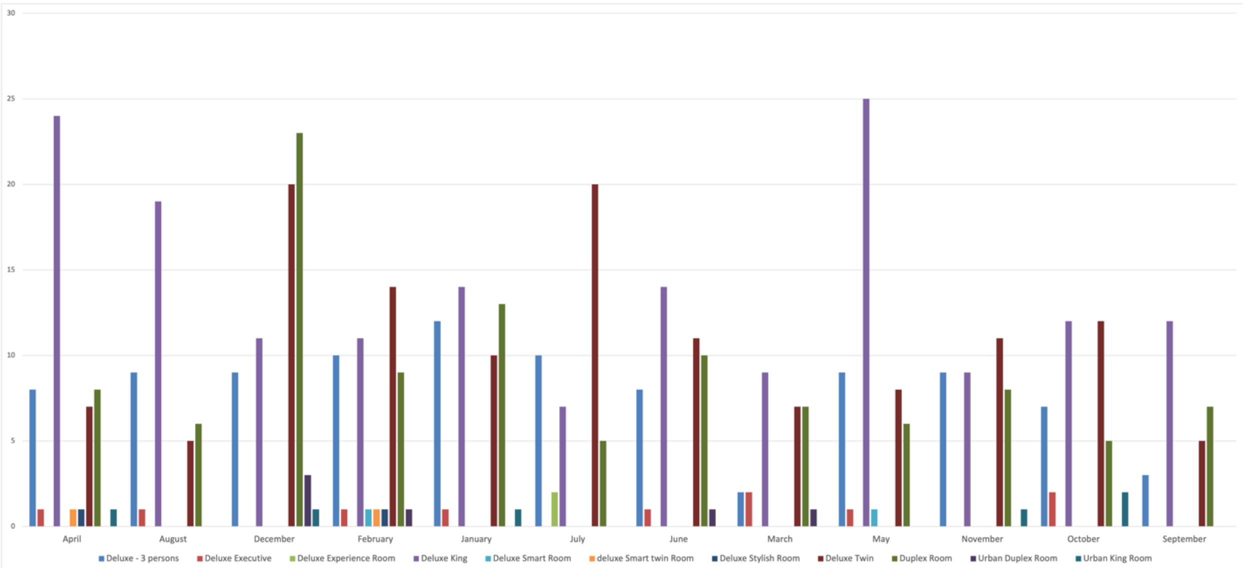

Figure 5. Room Type based on Month of Stay (530 Accounts)

Figure 5 presents a detailed breakdown of room type preferences by guests according to the month of stay, based on data from 530 accounts. The graph indicates noticeable variations in room selection patterns throughout the year,

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with certain months showing a clear preference for specific room categories. For instance, deluxe and superior rooms tend to see higher bookings during peak travel months, which may correlate with increased tourism activity or holiday seasons. The fluctuations in room type choices suggest that guests' preferences are likely influenced by seasonal promotions, special events, or changing traveler demographics throughout the year. Additionally, the data reveals that suite rooms experience relatively consistent demand, potentially driven by business travelers or those seeking luxurious accommodations. Analyzing these trends is crucial for hotel management to optimize inventory allocation, tailor marketing strategies, and adjust pricing dynamically in response to demand patterns. This approach ensures more efficient use of resources, enhances guest satisfaction, and contributes to maximizing revenue streams across different periods of the year.

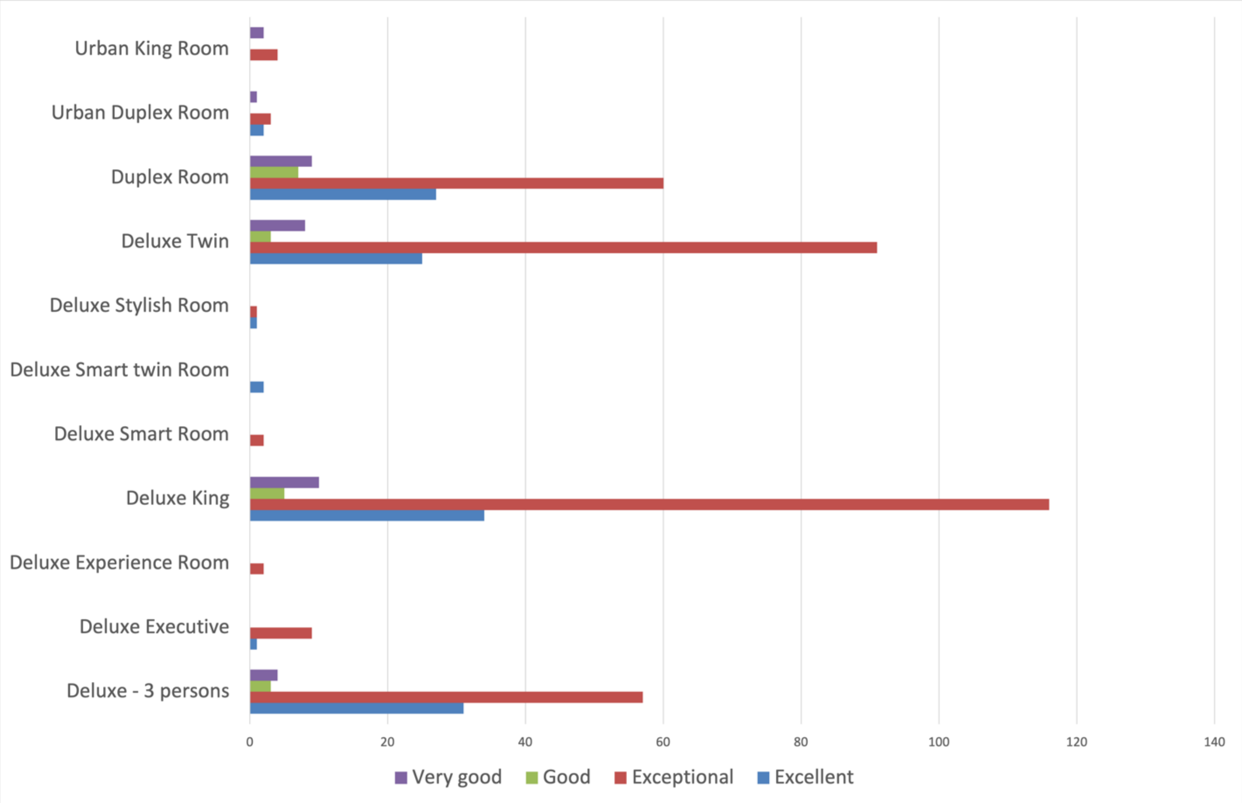

Figure 6. Rating based on Room Type (530 Accounts)

Figure 6 illustrates the distribution of customer ratings across various room types based on feedback from 530 accounts, providing insights into guest satisfaction levels. The data reveals that Deluxe Twin and Deluxe King rooms received the highest "Exceptional" ratings, suggesting these room categories are particularly successful in meeting or exceeding guest expectations. Meanwhile, Duplex and Deluxe Smart rooms primarily garnered "Very Good" and "Good" ratings, indicating a generally positive reception but with potential areas for enhancement to achieve higher satisfaction levels. Notably, Urban King and Urban Duplex rooms have relatively fewer ratings overall, which could imply limited bookings or a niche appeal to a specific segment of guests. The predominance of high ratings in the Deluxe categories suggests that guests prioritize spaciousness, comfort, and premium amenities, which these rooms likely offer. Analyzing these patterns is critical for hotel management to identify strengths and areas for improvement, guiding decisions on room upgrades, marketing strategies, and service enhancements. This focus on optimizing guest satisfaction based on feedback trends ensures better alignment with customer preferences, ultimately fostering loyalty and encouraging repeat bookings.

Analyzing guest demographics, room type preferences, and associated ratings provides a valuable basis for assessing customer satisfaction with the hotel's products and services. By examining these patterns, it becomes possible to discern the factors that contribute to positive or negative guest experiences, which, in turn, can inform strategies to optimize offerings. However, to transform this descriptive data into actionable insights, a more sophisticated approach is required to predict sentiment effectively. Applying a CNN-LSTM model architecture, enhanced by SMOTE to address class imbalances, offers a promising method for predicting customer sentiments based on review data. Such predictive modeling can significantly enhance the hotel's ability to proactively improve service quality, refine product offerings, and develop targeted marketing strategies. By leveraging these insights, the hotel can elevate customer satisfaction and achieve a competitive advantage in an increasingly customer-centric market.

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3. RESULT AND DISCUSSION

3.1 Evaluation of CNN-LSTM and SMOTE in Sentiment Classification of Hotel Reviews Data

The evaluation of the hybrid CNN-LSTM model combined with SMOTE for sentiment classification of hotel reviews demonstrates its effectiveness in addressing data imbalance while optimizing classification accuracy. This approach leverages CNN's capability to extract spatial features from text and LSTM's strength in capturing long-term dependencies, thus enhancing the model's comprehension of complex sentiment patterns. By applying SMOTE, the dataset's class distribution is balanced, which mitigates the risk of biased predictions and ensures a more equitable representation of positive, negative, and neutral sentiments. This integration is especially crucial in hotel review analysis, where an overrepresentation of positive feedback could obscure critical insights from minority classes. The evaluation metrics, including precision, recall, and F1-score, indicate a significant improvement in model performance compared to traditional methods. Such findings underscore the model's potential to provide accurate sentiment analysis, thereby enabling hotels to gain deeper insights into customer satisfaction and areas for service enhancement. This approach improves predictive reliability and supports data-driven decision-making in the hospitality industry.

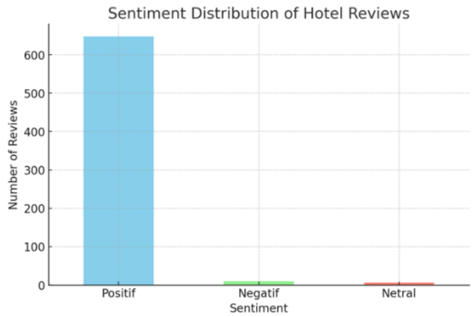

Figure 7. Sentiment Distribution of the 101 Bandung Dago Hotel Reviews (664 Accounts)

Figure 7 presents the sentiment distribution of customer reviews for THE 101 Bandung Dago Hotel, derived from 664 accounts. The analysis reveals a predominant inclination towards positive sentiment, with an overwhelming majority of reviews classified as positive. This trend suggests high customer satisfaction, reflecting positively on the hotel's service quality, amenities, and overall guest experience. In contrast, the proportion of negative and neutral sentiments remains notably low, indicating that unfavorable feedback is rare. Such a skewed distribution may imply that the hotel has successfully met or exceeded most guests' expectations, fostering positive impressions. However, the minimal presence of negative and neutral sentiments, though minor, highlights areas that might still benefit from targeted improvements to enhance overall guest satisfaction. By understanding the sentiment landscape, management can refine their service offerings to maintain high satisfaction levels and address any subtle concerns indicated in the less frequent negative feedback, ultimately supporting continuous improvement in guest relations.

Based on the implementation of the CNN-LSTM model combined with SMOTE, using an 80% training and 20% testing data split, the training history indicates distinct trends in model performance. The accuracy graph shows that while training accuracy consistently improves across epochs, the validation accuracy plateaus after initial increases, indicating potential overfitting as the model becomes more specialized to the training data. Conversely, the loss graph reveals that training loss decreases steadily, while validation loss diverges after a few epochs, reflecting the model's decreasing generalization ability to unseen data. This pattern suggests that while the model effectively learns from the training set, it may struggle to generalize to new inputs, likely due to overfitting. These results emphasize the need for further hyperparameter tuning or regularization techniques to enhance the model's robustness, thus achieving a better balance between training performance and validation accuracy. Such optimization is crucial for ensuring the sentiment classification model remains accurate and generalizable when applied to real-world hotel review data.

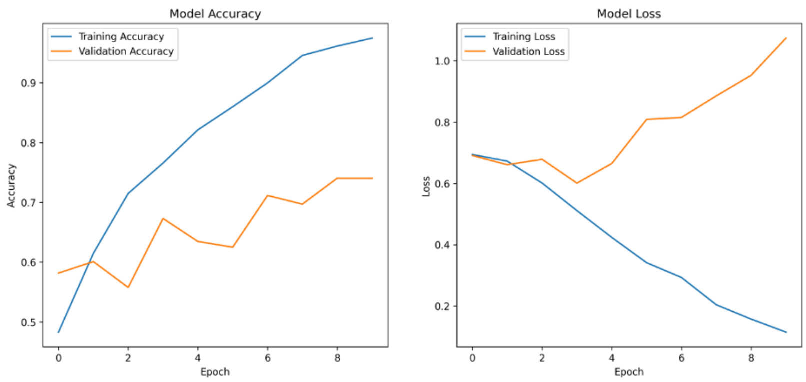

Figure 8. Training History (a and b)

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Figure 8 displays the training history of a machine learning model, highlighting clear signs of overfitting. In the left graph, the blue line representing training accuracy shows a steady increase, surpassing 90%, which suggests that the model fits the training data exceptionally well. In contrast, the orange line, indicating validation accuracy, plateaus around 70% without significant improvement, signaling that the model struggles to generalize beyond the training dataset. Meanwhile, the right graph illustrates the loss metrics, where the blue line (training loss) continuously decreases, indicating that the model minimizes errors on the training set. However, the orange line (validation loss) initially decreases but begins to rise after the second epoch, reflecting a divergence in model performance. This pattern is characteristic of overfitting, where the model becomes too specialized to the training data, capturing noise instead of underlying patterns. As a result, while it performs exceptionally well on the training set, its ability to handle new, unseen data is compromised. The widening gap between training and validation performance underscores the need for strategies like regularization or dropout layers to improve the model's capacity for generalization, thus enhancing its robustness in real-world applications.

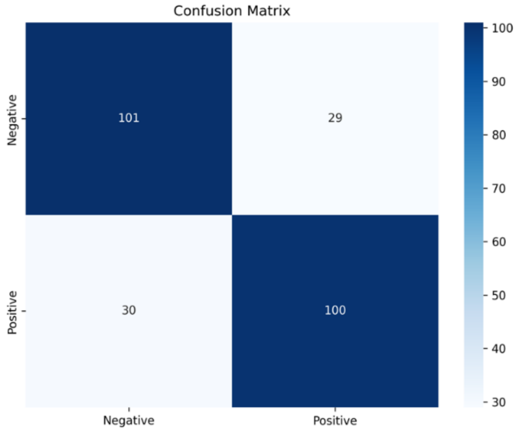

Figure 9. Confusion Matrix

Figure 9 presents a confusion matrix that evaluates the performance of a binary classification model distinguishing between positive and negative sentiments. The matrix reveals that the model correctly predicted 101 instances as unfavorable (true negatives) and 100 instances as positive (true positives), indicating a relatively strong performance in identifying both classes accurately. However, there are some misclassifications, with 29 cases where the model falsely predicted a positive sentiment for actual negative instances (false positives) and 30 cases where positive reviews were incorrectly classified as unfavorable (false negatives). These misclassification rates contribute to Type I and Type II errors, respectively, which affect the overall model effectiveness. The computed accuracy of the model stands at 77%, derived from the ratio of correct predictions to total predictions. Additionally, precision and recall metrics are approximately 78% and 77%, respectively, reflecting the model's balanced ability to identify true positives while minimizing false alarms. The F1 score, which harmonizes precision and recall, is calculated at 77.5%, indicating a well-rounded performance. While the results demonstrate a reasonable balance between sensitivity and specificity, there remains potential for optimization to reduce error rates and enhance predictive accuracy further.

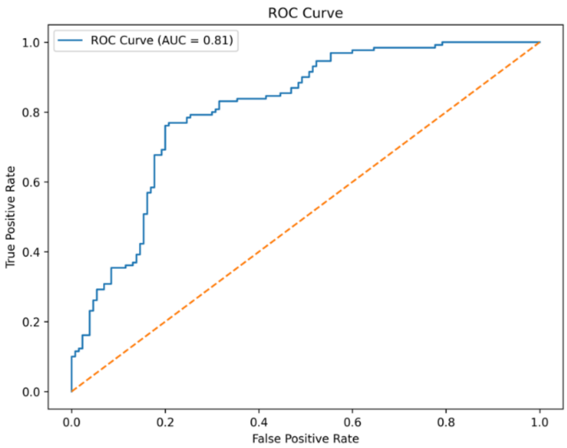

Figure 10. Receiver Operating Characteristic (ROC) Curve

Figure 10 presents the Receiver Operating Characteristic (ROC) curve, which is a graphical representation used to assess the performance of a binary classification model. The blue curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings, demonstrating the model's ability to differentiate between positive and negative classes. The Area Under the Curve (AUC) is calculated at 0.81, indicating that the

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model performs significantly better than random guessing, represented by the orange dashed baseline with an AUC of 0.5. An AUC score above 0.8 generally indicates a robust classification capability, suggesting that the model is 81% effective at distinguishing between the two classes. The pronounced bend of the ROC curve towards the top-left corner reflects a high sensitivity while maintaining a relatively low false positive rate, signifying discriminatory solid power. However, the trade-off between TPR and FPR becomes evident as the curve progresses to the right, where an increase in false alarms accompanies gains in sensitivity. The optimal point is typically found where the curve starts to flatten, balancing detection accuracy with minimizing false positives. The model demonstrates reliable performance, making it suitable for applications where a balance between sensitivity and specificity is crucial, such as customer sentiment analysis in service-oriented industries.

The model performance analysis indicates the presence of overfitting, which is particularly noticeable after the second epoch. While the training accuracy exceeds 90%, the validation accuracy plateaus around 70% and the training loss continues to decline while validation loss begins to rise. This divergence suggests that the model is overly fitting the training data at the expense of generalization to new data. Addressing this issue would benefit from implementing regularization techniques, dropout layers, or early stopping around the second or third epoch to prevent the model from overfitting further. Regarding classification performance, the confusion matrix reveals a balanced yet imperfect classification with an overall accuracy of 77%. Precision and recall are closely aligned at 78% and 77%, respectively, leading to an F1 score of 77.5%. Despite the relatively balanced detection of positive and negative classes, 29 false positives and 30 false negatives suggest room for refinement. The ROC curve analysis further highlights the model's discriminatory strength, with an AUC score of 0.81, significantly above the random baseline of 0.5. This score reflects the model's robust capability to distinguish between positive and negative sentiments, indicating that while the model performs well, enhancements in its generalization could further optimize its overall accuracy and reliability in real-world applications.

3.2 Discussion

The hybrid CNN-LSTM model has demonstrated commendable performance in classifying sentiment based on hotel guest reviews, effectively leveraging the strengths of both convolutional and recurrent layers. The CNN component excels at extracting local textual features, capturing nuanced expressions within the reviews. In contrast, the LSTM component proficiently handles sequential dependencies, allowing the model to grasp context over extended text sequences [36]. This combination enables a deeper understanding of customer sentiments, capturing explicit opinions and subtle cues. The model's architecture addresses common challenges in sentiment analysis, such as distinguishing between closely related sentiments and managing the inherent variability in natural language. The model can balance sensitivity and specificity by achieving high precision and recall, ensuring that positive and negative sentiments are accurately identified. The results suggest that this hybrid approach enhances predictive accuracy and provides a reliable tool for extracting actionable insights from guest feedback, which is crucial for optimizing customer satisfaction strategies in the hospitality sector.

The implementation of SMOTE (Synthetic Minority Over-sampling Technique) significantly enhances sentiment analysis by addressing the challenge of imbalanced datasets, which is a common issue in text classification tasks. In sentiment analysis, a disproportionate number of positive reviews often overshadows negative or neutral ones, leading to biased model predictions and reduced accuracy in identifying minority class sentiments. By generating synthetic samples for underrepresented classes, SMOTE ensures a more balanced dataset, thereby improving the model's ability to recognize diverse sentiment expressions [37]. This technique is particularly beneficial in preventing the model from overfitting to the majority class, which would otherwise compromise its performance on less frequent sentiment categories. The balanced distribution achieved through SMOTE results in more accurate classification metrics, such as precision and recall, especially for the minority classes. Consequently, this approach enhances the robustness of the sentiment analysis model. It ensures that customer feedback is interpreted more comprehensively, enabling nuanced insights for strategic decision-making in customer-focused industries.

Implementing a CNN-LSTM model combined with SMOTE offers substantial benefits in predicting sentiment from hotel review data, enabling more precise data processing tailored to specific customer feedback. By leveraging CNN's capability to extract detailed textual features and the LSTM's strength in capturing sequential patterns, this hybrid model efficiently analyzes complex review texts, uncovering more profound insights into customer sentiment [38]. The use of SMOTE further enhances the model's robustness by addressing the issue of data imbalance, which often skews analysis towards the majority class, resulting in a more accurate representation of diverse customer opinions. Such a refined approach to sentiment analysis equips hotel management with actionable insights, enabling them to identify strengths and address areas needing improvement in their products and services. By understanding the nuances in customer feedback, hotels are better positioned to enhance customer satisfaction, adapt their offerings to meet evolving demands, and ultimately strengthen their competitive edge in the hospitality market.

The outputs generated from sentiment classification provide invaluable insights for decision-makers in comprehending the current state of the hotel as perceived by guests. This understanding enables management to identify critical areas that significantly impact customer satisfaction and address potential shortcomings highlighted by the feedback. By analyzing patterns in guest sentiment, hoteliers can discern which aspects of their services resonate positively with guests and which elements require enhancement. Such data-driven insights are crucial for refining service quality and pinpointing specific factors contributing to satisfaction or dissatisfaction. In this way,

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sentiment analysis is a strategic tool that guides targeted improvements in service offerings and ensures that the hotel's operations align more closely with guest expectations. This approach enhances the guest experience and fosters customer loyalty, supporting long-term business sustainability in the competitive hospitality industry.

4. CONCLUSION

In conclusion, this research, conducted on customer reviews for THE 1O1 Bandung Dago Hotel, illustrates the effectiveness of employing a hybrid CNN-LSTM model integrated with the Synthetic Minority Over-sampling Technique (SMOTE) to enhance sentiment classification accuracy. Addressing challenges related to unstructured textual data and class imbalances, the study utilized a dataset of 665 reviews sourced from the Agoda platform, applying an 80% training and 20% testing split, which resulted in 532 training reviews and 133 testing reviews. By leveraging SMOTE to balance the dataset, the model achieved an overall accuracy of 77%, correctly classifying 201 out of 231 positive reviews (87%) and 101 out of 131 negative reviews (77%), with 29 false positives (13%) and 30 false negatives (23%). Additionally, the F1 score stood at 77.5%, with precision at 78% and recall at 77%, while the ROC curve yielded an AUC score of 0.81, indicating discriminatory solid capability. These findings demonstrate the hybrid model's potential to derive actionable insights from customer feedback, allowing hotels to enhance service quality and customer satisfaction. Optimizing the model by exploring hyperparameter tuning, regularization techniques, or incorporating attention mechanisms is recommended for further research to mitigate overfitting and improve generalization. Additionally, expanding the application of this model to include reviews from various hotel types or other service-oriented sectors could validate its versatility across different domains. Multilingual datasets would enhance sentiment detection for international guests, making the analysis more comprehensive. Further exploration of aspect-based sentiment analysis could provide granular insights into specific areas of guest satisfaction, such as service, cleanliness, or amenities. Moreover, implementing this model for real-time sentiment analysis could empower hotels to adjust services dynamically based on customer feedback. These recommendations aim to refine sentiment analysis techniques, supporting data-driven strategies for improving customer experiences and competitive positioning in the hospitality industry.

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