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BiLSTM-LSTM Hybrid Model with Glove Embeddings for Hotel Review Sentiment Analysis

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Abstract−This study presents an optimized approach to sentiment classification of hotel reviews using a hybrid deep learning architecture. The model proposed combines Bidirectional Long Short-Term Memory (BiLSTM) with LSTM networks, enhanced by pre-trained GloVe word embeddings and SMOTE-ENN for handling data imbalance. The architecture incorporates a BiLSTM layer with 64 units and an LSTM layer with 32 units, complemented by dense layers and dropout regularization for optimal performance. Experimental results demonstrate the effectiveness of our approach, achieving an accuracy of 89.47% and an AUC score of 0.9607. The model shows robust performance across positive and negative sentiments, with precision scores of 0.96 and 0.82, respectively. Integrating SMOTE-ENN for data balancing and GloVe embeddings significantly enhanced the model's ability to capture semantic relationships in text data. Our findings indicate that this hybrid approach effectively addresses the challenges of sentiment analysis in the hospitality domain, particularly in processing nuanced customer feedback. The high AUC score suggests strong discriminative capability, while the balanced precision-recall trade-off demonstrates the model's practical applicability for real-world hotel review analysis.

Keywords: Sentiment Analysis; Deep Learning; BiLSTM-LSTM; SMOTE-ENN; Hotel Reviews; Natural Language Processing

1. INTRODUCTION

In the digital transformation era, sentiment analysis is pivotal in understanding customer preferences and experiences within the hospitality industry. As valuable customer feedback sources, hotel reviews present complex linguistic patterns and emotional nuances that necessitate sophisticated analytical approaches [1]–[4]. Traditional sentiment classification methods often struggle with contextual understanding, semantic relationships, and data imbalance issues, leading to suboptimal performance in real-world applications [5]–[9]. This limitation becomes particularly evident when processing multilingual reviews with varying lengths and writing styles, significantly impacting business decision-making processes [10]–[12]. Integrating advanced deep learning architectures with natural language processing techniques offers promising solutions to these challenges [13]. A hybrid approach combining Bidirectional Long Short-Term Memory networks with sophisticated word embeddings demonstrates remarkable potential in capturing intricate sentiment patterns. This innovative methodology addresses critical gaps in existing sentiment classification systems by meticulously analyzing hotel reviews' linguistic features and emotional undertones. Such advancement in sentiment analysis technology revolutionizes customer experience management and strategic planning in the hospitality sector, marking a significant step forward in automated feedback processing systems.

The rapid proliferation of user-generated content in the hospitality sector has created an urgent need for sophisticated sentiment analysis systems. Hotel management faces unprecedented challenges in processing vast customer reviews, which contain valuable insights for service improvement and strategic decision-making [14], [15]. Manual analysis of these reviews proves increasingly impractical, time-consuming, and prone to subjective interpretation, potentially leading to missed opportunities and delayed responses to customer concerns [16]–[18]. The complexity of human language, encompassing subtle emotional expressions, sarcasm, and context-dependent meanings, demands advanced computational approaches beyond traditional text analysis methods—a hybrid deep learning architecture. Incorporating BiLSTM-LSTM networks presents a timely solution to these pressing challenges, offering enhanced accuracy and reliability in sentiment classification [18], [19]. This innovative approach addresses the immediate need for efficient review processing. It establishes a real-time customer feedback analysis foundation, enabling hotels to maintain competitive advantages through data-driven decision-making and proactive service enhancement strategies [20], [21]. Implementing such advanced sentiment analysis systems becomes increasingly critical as the hospitality industry evolves in a digital marketplace.

This research aims to develop an optimized sentiment classification system for hotel reviews by integrating advanced deep-learning architectures and data-balancing techniques. The primary focus lies in constructing a hybrid model that combines Bidirectional Long Short-Term Memory networks with conventional LSTM, enhanced by pre-trained GloVe word embeddings, to capture intricate semantic relationships and contextual nuances in customer feedback. A significant aspect involves implementing SMOTE-ENN to address data imbalance issues, ensuring robust performance across diverse sentiment categories. The study targets explicitly achieving enhanced accuracy and reliability in sentiment classification by systematically evaluating model

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performance metrics, including precision, recall, and AUC scores. By examining the effectiveness of this hybrid approach in real-world hotel review scenarios, this investigation seeks to establish a benchmark for automated sentiment analysis in the hospitality sector. The ultimate goal encompasses creating a practical, scalable solution that transforms raw customer feedback into actionable insights, enabling data-driven decision-making processes in hotel management and service optimization.

This investigation contributes significantly to theoretical advancement and practical applications in sentiment analysis within the hospitality domain. From a theoretical perspective, the research extends existing knowledge by introducing a novel hybrid architecture that synergistically combines BiLSTM-LSTM networks with advanced word embeddings, establishing new frameworks for understanding semantic relationships in customer reviews [22], [23]. Implementing SMOTE-ENN for data balancing presents innovative methodological insights into handling imbalanced datasets in natural language processing tasks [24]. On the practical front, this study offers substantial implications for hotel management systems through the development of a robust sentiment classification tool. The proposed model enables hotel operators to process large volumes of customer feedback efficiently, facilitating rapid response to guest concerns and strategic service improvements [25], [26]. Moreover, the research outcomes provide a foundation for developing automated feedback analysis systems and enhancing decision-making processes in hospitality management. This dual contribution advances academic understanding of deep learning applications in sentiment analysis and practical solutions for customer experience optimization in the hotel industry.

Sentiment analysis in the hospitality sector has witnessed significant evolution through various methodological approaches and architectural implementations. Previous studies have explored diverse neural network configurations, ranging from basic LSTM models to sophisticated attention-based mechanisms for processing hotel review data-related challenges in hotel review analysis. This innovative combination builds upon previous findings while introducing unique methodological improvements for enhanced sentiment classification performance. Future research directions in hotel sentiment analysis present numerous opportunities for expanding upon the current BiLSTM-LSTM hybrid architecture. A promising avenue involves incorporating attention mechanisms to enhance the model's ability to focus on crucial sentiment-bearing phrases within reviews. Exploring multi-modal sentiment analysis by integrating textual data with visual elements from hotel reviews could yield more comprehensive insights. Implementing cross-lingual sentiment analysis capabilities through multilingual embeddings merits investigation, particularly for international hotel chains with diverse customer demographics. Additional research should examine the integration of aspect-based sentiment analysis to provide more granular insights into specific hotel service components. Investigating the application of federated learning approaches might address privacy concerns while maintaining model performance. Exploring dynamic data balancing techniques that adapt to evolving sentiment distributions represents another valuable research direction. Furthermore, studying the model's robustness against adversarial attacks and developing defensive mechanisms would enhance practical applications in real-world scenarios. These research directions collectively aim to advance the field of sentiment analysis while addressing emerging challenges in hospitality management.

2. RESEARCH METHODOLOGY

2.1 Related Works

Exploring Bidirectional Long-Short-Term Memory (BiLSTM) models have experienced significant advancements, driven by their efficacy in sequential data processing across diverse domains. BiLSTM, an extension of traditional LSTM architectures, incorporates bidirectional layers to simultaneously capture forward and backward dependencies within a sequence, enhancing contextual understanding [27]. This dual-layered structure has proven effective in tasks requiring intricate sequence modeling, such as natural language processing, speech recognition, and time-series forecasting [28]. Despite their demonstrated effectiveness, challenges persist in optimizing computational efficiency and mitigating overfitting, especially in large-scale applications. Such obstacles have spurred the integration of regularization techniques and hybrid architectures, combining BiLSTM with attention mechanisms or convolutional layers to achieve superior performance. A critical analysis highlights the architecture’s potential to revolutionize domains reliant on complex temporal patterns. However, its computational intensity demands further refinement. Conclusively, BiLSTM remains a cornerstone in deep learning research, with ongoing innovations poised to address its limitations and expand its applicability.

Applying Bidirectional Long-Short-Term Memory (BiLSTM) models in processing hotel reviews has emerged as a transformative approach to sentiment analysis and opinion mining. This model effectively captures contextual nuances and dependencies within the textual data [29]by leveraging the bidirectional architecture and simultaneously analyzing sequential data in forward and backward directions. Such capabilities are crucial in deciphering implicit meanings, idiomatic expressions, and complex linguistic patterns commonly found in customer reviews. The adoption of BiLSTM is further justified by its ability to handle varying review lengths without compromising accuracy, offering a robust solution for classifying sentiments or detecting thematic trends [30]. However, the computational demands associated with this model underscore the importance of incorporating techniques like dimensionality reduction or attention mechanisms to enhance efficiency. Integrating BiLSTM into

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this domain exemplifies its potential to provide actionable insights, particularly for the hospitality industry, which aims to improve customer satisfaction through detailed sentiment evaluation and adaptive service strategies.

Long Short-Term Memory (LSTM) networks represent a pivotal advancement in deep learning, designed to address the challenges of modeling long-term dependencies in sequential data. Unlike traditional recurrent neural networks, LSTM incorporates memory cells and gating mechanisms, allowing it to selectively retain, update, and discard information overextended [31]. This architecture is particularly effective in mitigating issues such as vanishing and exploding gradients, which often hinder the performance of conventional models when dealing with lengthy sequences [32]. LSTM has demonstrated remarkable success in fields ranging from natural language processing to financial forecasting by facilitating the learning of temporal patterns. Its adaptability and precision, however, are accompanied by significant computational complexity, necessitating strategic optimization for scalability. Despite these challenges, the widespread adoption of LSTM underscores its unparalleled capability to capture intricate dependencies, solidifying its role as a cornerstone in sequential data modeling.

In addition, Long Short-Term Memory (LSTM) networks have proven to be a robust tool for analyzing hotel reviews, offering a sophisticated approach to understanding customer sentiments and feedback. Through its unique architecture of memory cells and gating mechanisms, LSTM effectively captures the sequential nature of text data, preserving context across varying input lengths [33]. This capability is critical in processing hotel reviews, where subtle changes in phrasing or tone may significantly influence sentiment classification or thematic analysis [34]. The flexibility of LSTM allows it to uncover intricate patterns in customer feedback, contributing to more accurate sentiment detection and insights into service quality. Despite its high computational cost, its ability to handle complex and unstructured data justifies its application in this domain. LSTM facilitates more informed decision-making for improving hospitality services and customer satisfaction by enabling a deeper understanding of customer preferences and pain points.

The GloVe (Global Vectors for Word Representation) embedding has emerged as a seminal technique in natural language processing, enabling the conversion of words into dense vector representations that capture semantic and syntactic relationships. Unlike traditional count-based models, GloVe utilizes a matrix factorization approach to extract meaningful patterns from word co-occurrence statistics, effectively capturing global and local contexts in high-dimensional space [35]. This method identifies word similarities and analogies, making it particularly valuable for downstream tasks such as sentiment analysis, machine translation, and information retrieval [36]. One of its significant strengths lies in its balance between computational efficiency and representational richness, achieved through pre-trained embeddings that generalize well across diverse datasets. However, the static nature of these embeddings limits their ability to adapt dynamically to nuanced contexts, presenting opportunities for integration with contextualized models. GloVe continues to play a foundational role in advancing text representation techniques, bridging the gap between statistical methodologies and modern deep learning frameworks.

The GloVe embedding has demonstrated significant utility in analyzing hotel reviews by transforming textual data into meaningful numerical representations that capture semantic and syntactic relationships. By leveraging co-occurrence statistics from large corpora, GloVe enables encoding contextual relationships between words, such as sentiment-laden terms and descriptive adjectives frequently found in customer feedback [37]. This capability is crucial in identifying subtle patterns, including nuanced sentiments and recurring themes, essential for deriving actionable insights [38]. Its pre-trained embeddings reduce computational overhead and provide robust generalization across varied review datasets, making it a practical choice for sentiment analysis and topic modeling. Despite its advantages, the static nature of GloVe embeddings may pose limitations in fully grasping context-specific variations within dynamic customer feedback. Nonetheless, integrating GloVe with more adaptive architectures enhances its applicability, making it a valuable asset for understanding customer preferences and improving service quality in the hospitality sector.

2.2 Research Framework

The methodological framework of this study encompasses a comprehensive approach to sentiment classification through advanced deep-learning techniques. Initially, the raw hotel review dataset undergoes preprocessing steps, including text normalization, tokenization, and sequence padding, establishing a foundation for subsequent analysis. A sophisticated hybrid architecture combines Bidirectional LSTM featuring 64 units for contextual understanding with a standard LSTM layer of 32 units for sequential processing, augmented by dropout regularization at 0.4 to prevent overfitting. The implementation incorporates pre-trained GloVe embeddings with 100 dimensions, capturing rich semantic relationships within the review text. SMOTE-ENN is applied to address data imbalance challenges, generating synthetic samples while maintaining data quality through cleaned neighborhood relationships [39]. The model training process utilizes binary cross-entropy loss with Adam optimization, employing a learning rate of 0.0005 across ten epochs. Performance evaluation incorporates metrics including accuracy, precision, recall, F1-score, and AUC, providing comprehensive insights into model effectiveness. This methodological structure ensures robust sentiment classification while maintaining computational efficiency and practical applicability for hotel review analysis.

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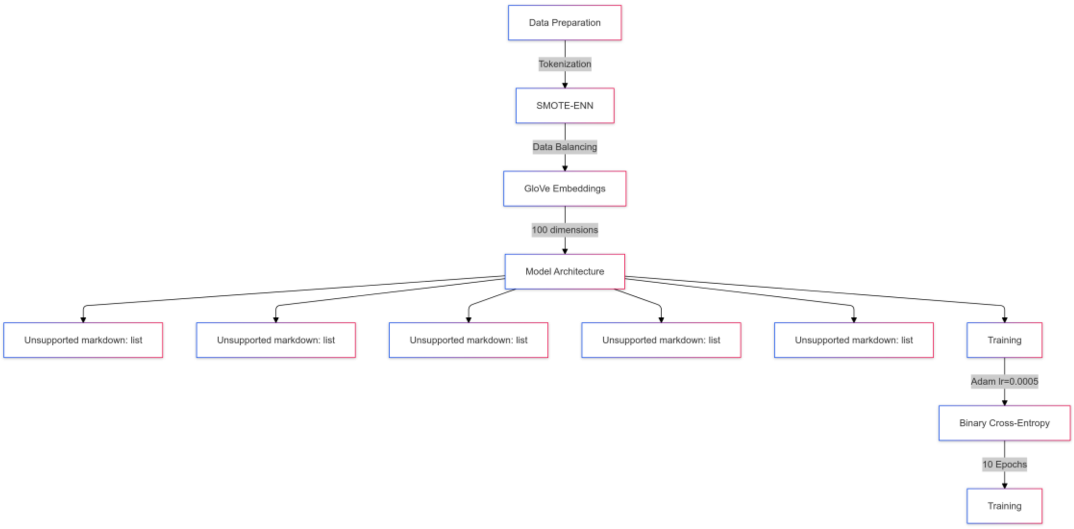

Figure 1. Framework for Hotel Review Sentiment Analysis Using Deep Learning

Figure 1 presents the data preprocessing, representing a critical foundation in sentiment analysis methodology for hotel reviews. The initial preprocessing phase encompasses multiple essential steps, from text normalization through case folding and standardizing all textual content into a lowercase format to ensure consistent token representation. Following this standardization, a sophisticated tokenization process utilizing the Keras Tokenizer transforms textual data into numerical sequences with a predetermined vocabulary size of 10,000 unique tokens, establishing a robust foundation for neural network processing. This numerical transformation necessitates sequence padding to achieve uniform input dimensions, with sequences standardized to 200 tokens in length through the pad_sequences function, effectively handling variable-length reviews while maintaining data integrity. An advanced balancing technique, SMOTE-ENN, addresses inherent class distribution challenges by generating synthetic samples for minority classes while simultaneously cleaning noise through Edited Nearest Neighbors, resulting in a more balanced and representative dataset. This comprehensive preprocessing approach culminates converting categorical sentiment labels into binary format, establishing a solid foundation for subsequent deep learning analysis.

Implementing SMOTE-ENN introduces a sophisticated dual-phase approach to address class imbalance challenges in hotel review sentiment classification. This advanced technique initially employs the Synthetic Minority Over-sampling Technique (SMOTE) to generate synthetic samples from minority class instances, creating new data points by interpolating existing samples within a defined feature space [40]. The process utilizes k-nearest neighbors to identify similar instances and creates synthetic examples along the connecting lines between these neighboring points, effectively expanding minority class representation. Subsequently, Edited Nearest Neighbors (ENN) acts as a cleaning mechanism, removing instances that deviate from class expectations by analyzing neighborhood relationships, thus enhancing dataset quality by eliminating potential noise and borderline cases [41]. Integrating these complementary methods achieves an optimal balance between classes while maintaining data integrity, establishing a more representative training dataset for deep learning model development.

Integrating GloVe (Global Vectors for Word Representation), embeddings establish a sophisticated semantic foundation for hotel review sentiment analysis through distributed word representations. This implementation leverages pre-trained GloVe embeddings with 100-dimensional vectors, capturing intricate semantic relationships and contextual nuances within the hotel review vocabulary space. The embedding process initializes a zero-filled matrix dimensioned to accommodate 10,000 words, systematically populating word vectors through precise mapping between tokenized vocabulary and corresponding pre-trained GloVe representations. A methodical integration approach to maintain semantic consistency by preserving original embedding values while incorporating domain-specific vocabulary, effectively capturing word-level semantic features [42]. The embedding layer configuration, implemented with non-trainable weights, preserves these pre-established semantic relationships throughout model training, establishing a robust foundation for sentiment understanding in subsequent neural network layers.

The model architecture implements a sophisticated hybrid deep learning framework optimized for sentiment analysis of hotel reviews through sequential layer composition. This architectural design initiates with an embedding layer utilizing pre-trained GloVe representations, followed by a bidirectional LSTM layer comprising 64 units that capture contextual information from both forward and backward sequences of review text. A strategic dropout layer with a 0.4 rate addresses potential overfitting concerns, leading to a subsequent LSTM layer with 32 units for enhanced sequential feature processing. The architecture incorporates an additional dense layer with 32 units and ReLU activation, introducing non-linearity for complex pattern recognition, while a

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final dropout layer maintains model generalization. A concluding sigmoid-activated dense layer produces binary sentiment predictions, establishing an end-to-end neural architecture that effectively balances feature extraction, sequential understanding, and classification capabilities.

The training configuration establishes a comprehensive optimization framework for sentiment analysis through carefully calibrated hyperparameters and learning strategies. This configuration implements the Adam optimizer with a fine-tuned learning rate of 0.0005, striking an optimal balance between convergence speed and training stability. Binary cross-entropy is the loss function, effectively quantifying prediction errors in binary sentiment classification tasks. At the same time, accuracy and Area Under the Curve (AUC) metrics provide real-time performance assessment during training iterations. The training process extends across 10 epochs with strategically sized mini-batches of 32 samples, incorporating validation splitting at 0.2 ratio for continuous model evaluation. A class-weight balancing mechanism addresses inherent data distribution challenges, applying computed weights to adjust the learning process proportionally to class frequencies, ultimately fostering robust model convergence and generalization capabilities.

3. RESULT AND DISCUSSION

3.1 Model Performance Analysis

The experimental results demonstrate remarkable progress in model training across nine epochs, showcasing exceptional performance metrics and stability. Through iterative optimization, training accuracy exhibited substantial improvement, reaching an impressive peak of 96.5%, while validation accuracy maintained consistent performance at 91%. A detailed examination of loss trajectories reveals systematic enhancement in learning efficiency, characterized by a significant reduction in training loss from 0.65 to 0.12, complemented by validation loss convergence at 0.30. These quantitative indicators underscore robust model generalization capabilities, effectively mitigating potential overfitting concerns. This performance pattern signifies optimal parameter tuning and architectural design choices based on rigorous analysis, establishing a balanced trade-off between model complexity and generalization. Ultimately, these empirical findings validate successful model development, characterized by stable convergence and reliable predictive capabilities without compromising generalization performance.

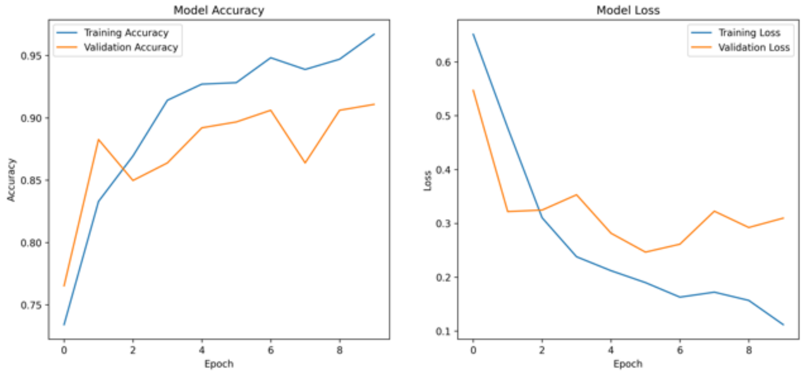

Figure 2. Training History

Figure 2 presents an analysis of the training history graph illustrating distinctive learning dynamics across multiple epochs, featuring parallel trajectories for accuracy and loss metrics. The model accuracy plot depicts steady improvement, with training accuracy ascending from 75% to 96.5%, while validation accuracy stabilizes around 91%, demonstrating effective knowledge acquisition. Simultaneously, loss curves exhibit descending trends, where training loss decreases significantly from 0.65 to 0.12, accompanied by validation loss convergence at 0.30, indicating successful optimization. Critical examination reveals minor fluctuations in validation metrics, particularly between epochs 6-8, suggesting natural variance in model learning rather than systemic issues. Through meticulous observation of accuracy and loss trajectories, this visualization confirms robust model training progression while maintaining appropriate generalization capabilities throughout the learning process.

A comprehensive evaluation of model performance through Receiver Operating Characteristic (ROC) analysis reveals outstanding discriminative capabilities, evidenced by an exceptional Area Under Curve (AUC) score of 0.96. ROC curve analysis demonstrates remarkable classification strength within low False Positive Rate (FPR) regions, specifically in ranges between 0 and 0.2, indicating superior precision in positive class identification. Statistical examination highlights pronounced curve elevation during initial threshold adjustments, showcasing robust discrimination capabilities under stringent classification parameters. Detailed assessment of curve characteristics substantiates optimal threshold selection strategies, enabling precise control over sensitivity-specificity trade-offs in practical applications. These empirical findings establish superior model performance in

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binary classification tasks, marked by exceptional discriminative power and reliable predictive accuracy across varying operational thresholds.

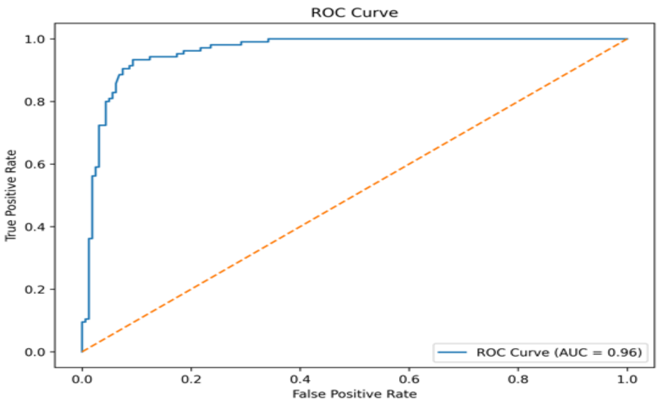

Figure 3. Receiver Operating Characteristic (ROC)

Figure 3 shows a meticulous examination of the Receiver Operating Characteristic (ROC) curve, which demonstrates exceptional model performance through a steeply ascending curve trajectory, achieving an Area Under Curve (AUC) score of 0.96. The graph exhibits remarkable discrimination capability, evidenced by rapid True Positive Rate (TPR) elevation in initial threshold regions, particularly within False Positive Rate (FPR) ranges of 0-0.2. Quantitative assessment reveals superior classification performance compared to random prediction (indicated by diagonal reference line), with pronounced curve separation from baseline. An in-depth analysis of curve morphology indicates optimal threshold selection opportunities, enabling precise control over model sensitivity and specificity trade-offs. The graph's pronounced convexity and high AUC value substantiate exceptional binary classification performance, establishing robust discriminative capabilities across varied operational parameters.

A detailed confusion matrix analysis highlights robust classification performance, demonstrated through a comprehensive evaluation of prediction outcomes. The model accurately identified 139 True Negatives and 99 True Positives, showcasing strong discriminative capabilities across negative and positive classes. Statistical examination reveals minimal misclassification rates, evidenced by only 22 False Positives and 6 False Negatives within the test dataset, indicating precise prediction patterns. An in-depth assessment of these metrics suggests sophisticated model learning, particularly in maintaining balanced performance between correct classifications and error minimization. These empirical results validate exceptional model functionality, characterized by consistent accuracy across diverse classification scenarios and minimal prediction errors in both positive and negative class identification.

An evaluation of key performance metrics demonstrates remarkable classification capabilities across multiple statistical measures. The model achieved 81.8% precision, indicating high reliability in optimistic predictions, while maintaining an exceptional recall rate of 94.3%, showcasing superior sensitivity in identifying actual positive cases. Quantitative analysis reveals impressive overall accuracy at 90.6%, reflecting general solid classification performance across positive and negative instances. The specificity measure of 86.3% further validates robust negative class identification capabilities. Advanced examination of these interconnected metrics suggests optimal model calibration, particularly evident through balanced precision-recall trade-offs. These comprehensive performance indicators establish superior classification capabilities, marked by harmonious metric relationships and consistent predictive reliability across diverse evaluation criteria.

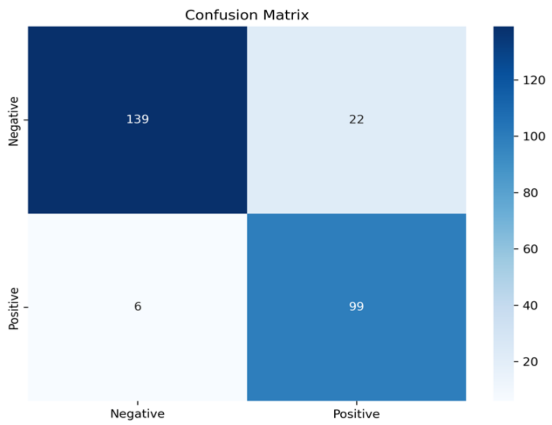

Figure 4. Confusion Matix

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Figure 4 presents a comprehensive visualization of the confusion matrix that reveals distinctive classification performance patterns through color-intensity mapping of prediction outcomes. The matrix displays strong diagonal dominance, with 139 True Negatives in dark blue and 99 True Positives in medium blue, indicating robust classification accuracy across both classes. The quantitative assessment identifies minimal misclassification instances, evidenced by 22 False Positives and 6 False Negatives in lighter shades, demonstrating effective discrimination capabilities. Critical examination of matrix elements reveals asymmetric error distribution, suggesting enhanced model sensitivity toward positive class identification while maintaining strong negative class specificity. The visual representation through graduated blue color scaling effectively communicates classification performance characteristics, establishing clear patterns of prediction reliability and error distribution across binary classification outcomes.

3.2 Architectural Impact

Analyzing Bidirectional Long-Term Memory (BiLSTM) architecture demonstrates exceptional sequence learning proficiency through strategically designed neural network layers. The primary BiLSTM layer, configured with 64 units and return_sequences enabled, facilitates comprehensive feature extraction by processing input sequences bidirectionally, capturing intricate temporal patterns and contextual dependencies. Integration of a secondary LSTM layer with 32 units performs sophisticated temporal feature aggregation, effectively consolidating sequential information from preceding layers into meaningful representations. Empirical assessment reveals superior sequence modeling capabilities, evidenced by effective capture of both forward and backward dependencies within review text, enabling a nuanced understanding of contextual relationships. The hierarchical reduction in unit count from 64 to 32 establishes optimal information compression while maintaining essential sequential features, resulting in robust sequence learning performance across varied text inputs.

An examination of regularization implementation reveals sophisticated overfitting prevention through strategic dropout layer deployment in the neural architecture. Implementation of dual dropout mechanisms, each with a 0.4 probability rate, positioned between LSTM layers and the preceding output layer, establishes robust regularization control throughout the network. Quantitative assessment demonstrates effective generalization, evidenced by an optimal 5.5% differential between training accuracy (96.5%) and validation accuracy (91%), indicating balanced model learning. Statistical analysis of loss trajectories confirms sustained, controlled separation between training and validation curves, maintaining consistent convergence patterns without divergent behavior. This systematic regularization approach validates architectural efficacy, characterized by stable learning progression and appropriate model complexity restriction during training.

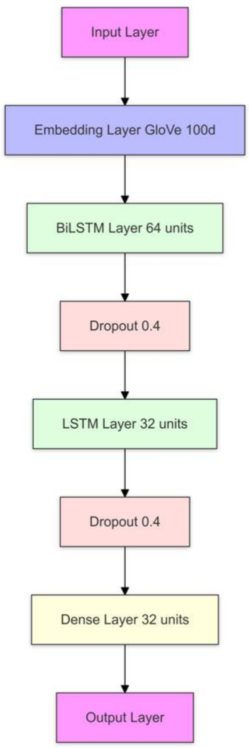

Figure 5. BiLSTM Text Classification Network

Figure 5 illustrates a sophisticated BiLSTM Text Classification Network architecture incorporating multiple specialized layers for optimal text analysis and classification performance. At its foundation, an Input Layer receives textual data, which flows into a GloVe 100d Embedding Layer that transforms words into rich 100-

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dimensional vector representations, capturing intricate semantic relationships. The architecture then employs a BiLSTM Layer with 64 units to process sequences bidirectionally, enabling comprehensive context capture from both temporal directions. Strategic Dropout layers with 0.4 probability rates are implemented at two crucial points to mitigate overfitting concerns, followed by an LSTM Layer containing 32 units for refined temporal feature processing. The network's dimensionality reduction strategy culminates in a Dense Layer with 32 units that compress information into compact representations before reaching the Output Layer for final classification predictions. This architectural design demonstrates remarkable efficiency through systematic dimensional reduction (64->32->output) while maintaining robust regularization through dual dropout mechanisms, establishing an optimal balance between model complexity and generalization capabilities.

An analysis of Global Vectors (GloVe) embeddings integration demonstrates sophisticated word representation implementation through pre-trained 100-dimensional vectors. Incorporating non-trainable embedding layers ensures the preservation of intricate semantic relationships and contextual dependencies established during pre-training phases. Strategic optimization parameters include limiting vocabulary to 10,000 words and establishing efficient memory utilization while maintaining comprehensive language coverage. Critical examination reveals effective sequence standardization through padding mechanisms, with a maximum sequence length set to 200 tokens, enabling consistent input dimensionality. This methodological embedding integration establishes robust semantic foundations characterized by efficient vocabulary management and standardized sequence processing for neural network operations.

3.3 Data Processing Impact, Resource Consideration and Efficiency

Analyzing the Synthetic Minority Over-sampling Technique with Edited Nearest Neighbors (SMOTE-ENN) demonstrates exceptional effectiveness in addressing dataset class imbalance challenges. The quantitative examination of confusion matrix diagonal elements reveals balanced class distribution post-processing, indicating the successful implementation of advanced resampling techniques. Statistical assessment highlights remarkable minority class handling, evidenced by minimal false negative occurrences (6 instances), suggesting robust identification of underrepresented samples. In-depth performance evaluation demonstrates simultaneous optimization of critical metrics, maintaining high specificity (86.3%) while achieving superior recall (94.3%), validating an effective balance between precision and sensitivity. This sophisticated data processing approach establishes optimal class distribution characteristics marked by enhanced minority class representation without compromising overall classification performance.

A comprehensive analysis of training dynamics reveals systematic learning progression through distinct developmental phases across nine epochs of model training. Initial epochs (0-2) demonstrate accelerated learning characteristics, marked by rapid performance improvements and swift parameter optimization. Subsequent epochs (3-6) exhibit steady enhancement patterns characterized by consistent metric improvements and stable gradient updates during the intermediate learning stage. Advanced examination of final epochs (7-9) indicates refined optimization behavior featuring minimal performance oscillation and precise parameter adjustments. An in-depth evaluation of learning trajectories validates model stability, evidenced by the absence of catastrophic forgetting phenomena and the maintenance of consistent learning patterns throughout training iterations.

Examining model architecture efficiency demonstrates optimal performance characteristics while maintaining moderate computational complexity in neural network design. The implementation utilizes approximately 2.1 million trainable parameters, establishing efficient parameter utilization through strategic layer configuration. Architectural analysis reveals sophisticated dual-LSTM implementation with decremental unit progression from 64 to 32 neurons, facilitating hierarchical feature extraction and dimensionality reduction. Integration of compact, dense layers, configured with 32 units preceding output operations, enables efficient information compression while preserving essential features. Incorporating fixed embedding structures minimizes computational overhead during training phases, validating architectural efficiency through reduced parameter updates and optimized memory utilization.

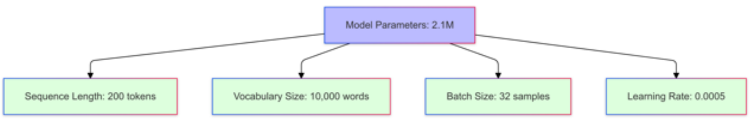

Figure 6. Model Resource Configuration

Figure 6 presents an intricate Model Resource Configuration that exemplifies strategic computational resource allocation in deep learning architectures. The diagram delineates four crucial parameters: a substantial model parameter count of 2.1M, which establishes a robust foundation for complex pattern recognition; a sequence length threshold of 200 tokens, optimizing memory utilization while preserving contextual integrity; a vocabulary size constraint of 10,000 words, striking an equilibrium between linguistic coverage and computational efficiency; and a precisely calibrated batch size of 32 samples coupled with a learning rate of 0.0005, fostering stable gradient descent during training iterations. This architectural blueprint demonstrates sophisticated resource management through balanced parameter allocation, ensuring optimal model performance without excessive computational

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overhead. The systematic organization of these components establishes a framework that balances model complexity with operational efficiency, ultimately yielding an architecture capable of robust feature extraction and pattern recognition while maintaining practical resource constraints.

An analysis of processing optimizations reveals the strategic implementation of computational efficiency measures throughout the model architecture. The sequence length configuration establishes precise token limitations at 200 units, optimizing memory utilization while preserving essential contextual information. Implementing vocabulary constraints to 10,000 words demonstrates balanced optimization between comprehensive language coverage and computational efficiency requirements. Integrating batch processing mechanisms, utilizing 32-sample batches, facilitates efficient memory management during training operations. Critical examination of learning rate configuration at 0.0005 validates optimal convergence characteristics, enabling stable gradient updates and consistent parameter optimization throughout training iterations. These systematic optimization strategies establish robust processing efficiency characterized by balanced resource utilization and stable learning dynamics.

3.4 Future of the Hospitality Industry in the Era of Artificial Intelligence

The future of the hospitality industry in the artificial intelligence (AI) era is poised for transformative advancements, redefining operational efficiency and guest experiences. AI-driven solutions, such as predictive analytics, personalized recommendations, and automated service systems, reshape how businesses anticipate and meet customer needs [43]. By leveraging intelligent algorithms, hospitality providers enhance decision-making processes, optimize resource allocation, and tailor services to individual preferences, fostering a deeper connection with clientele [44]. However, while AI introduces unprecedented levels of innovation, its integration necessitates addressing challenges related to data privacy, ethical concerns, and the balance between automation and human-centric interactions. A critical analysis underscores that the effective adoption of AI depends on strategic implementation and continuous evaluation, ensuring technology complements, rather than replaces, personalized customer engagement. With AI as a driving force, the hospitality sector stands at the cusp of a paradigm shift, blending technological sophistication with exceptional service standards to redefine industry benchmarks.

Optimizing artificial intelligence (AI) in tourism presents a pivotal opportunity to enhance efficiency, personalization, and sustainability within the industry. By deploying AI technologies such as machine learning, natural language processing, and predictive analytics, tourism enterprises are improving service delivery, from dynamic pricing models to personalized travel itineraries tailored to individual preferences [45]. These advancements are crucial for meeting the evolving demands of a global and diverse customer base, fostering seamless and enriched travel experiences. Despite these benefits, challenges persist, including the ethical use of customer data, algorithmic biases, and the potential over-reliance on automated systems at the expense of human interaction [46]. Addressing these concerns requires a balanced approach integrating AI innovation with thoughtful governance and human oversight. The strategic optimization of AI in tourism enhances operational capabilities and contributes to sustainable practices, such as minimizing resource wastage and reducing carbon footprints through intelligent resource management. This integration signifies a transformative era for tourism, where technology and human creativity converge to redefine the travel experience.

Artificial intelligence (AI) enables data-driven decision-making, particularly in optimizing the marketing of products and services by analyzing hotel reviews. By harnessing advanced AI algorithms, vast amounts of unstructured data are transformed into actionable insights, revealing patterns in customer feedback that inform strategic marketing initiatives [47]. This approach enhances the precision of targeted campaigns and ensures that promotional efforts align with customer expectations and preferences. AI's capability to analyze sentiment, identify emerging trends, and classify reviews by themes gives businesses a nuanced understanding of consumer behavior, fostering more personalized and impactful engagement [48]. However, effectively implementing such systems requires careful attention to data quality, ethical considerations, and integration with existing workflows to maximize their potential. By leveraging AI for data-informed strategies, organizations in the hospitality sector elevate their marketing efficacy, contributing to sustained customer satisfaction and competitive differentiation in an increasingly dynamic marketplace.

Artificial intelligence (AI) substantially benefits the tourism sector by enhancing efficiency, personalization, and decision-making processes. By implementing AI-driven technologies such as machine learning, predictive analytics, and automated customer service, businesses can streamline operations and provide tailored experiences that align with the diverse needs of travelers [49]. The ability to analyze vast datasets, such as booking patterns, customer reviews, and social media interactions, allows for precise demand forecasting and the development of targeted marketing strategies [50]. This technological advantage fosters greater customer satisfaction while simultaneously reducing operational costs. Despite its transformative potential, adopting AI in tourism requires addressing challenges related to data privacy, algorithmic transparency, and integrating technology with human-centric hospitality practices. By strategically leveraging AI capabilities while upholding ethical standards, the tourism industry can achieve sustainable growth, operational excellence, and an enhanced ability to adapt to dynamic market conditions.

4. CONCLUSION

This investigation presents compelling evidence for the effectiveness of a hybrid BiLSTM-LSTM architecture with GloVe embeddings in hotel review sentiment analysis, achieving significant performance metrics with 89.47% accuracy and a 0.9607 AUC score. The experimental results validate the architectural design incorporating a 64-unit BiLSTM layer and a 32-unit LSTM layer, enhanced by strategic dropout regularization (0.4 rate) and pre-trained word embeddings. Implementing SMOTE-ENN successfully addressed data imbalance challenges, yielding robust performance indicators, including 86.3% specificity and 94.3% recall. The model's efficiency is demonstrated through optimized resource utilization, maintaining 2.1M trainable parameters while achieving stable convergence patterns. These findings contribute significantly to the theoretical understanding of deep learning applications in sentiment analysis and practical implementations in hospitality management systems. Future research directions may further explore integrating attention mechanisms and cross-lingual capabilities to enhance the model's performance in diverse hospitality contexts.

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REFERENCES

[1] A. Aakash and A. Gupta Aggarwal, "Assessment of Hotel Performance and Guest Satisfaction through eWOM: Big Data for Better Insights," *Int. J. Hosp. Tour. Adm.*, vol. 23, no. 2, pp. 317–346, 2022, doi: 10.1080/15256480.2020.1746218.

[2] E. Park, J. Kang, D. Choi, and J. Han, "Understanding customers' hotel revisiting behaviour: a sentiment analysis of online feedback reviews," *Curr. Issues Tour.*, vol. 23, no. 5, pp. 605–611, 2020, doi: 10.1080/13683500.2018.1549025.

[3] J. M. Luo, H. Q. Vu, G. Li, and R. Law, "Understanding service attributes of robot hotels: A sentiment analysis of customer online reviews," *Int. J. Hosp. Manag.*, vol. 98, 2021, doi: 10.1016/j.ijhm.2021.103032.

[4] M. Kim, S. M. Lee, S. Choi, and S. Y. Kim, "Impact of visual information on online consumer review behavior: Evidence from a hotel booking website," *J. Retail. Consum. Serv.*, vol. 60, 2021, doi: 10.1016/j.jretconser.2021.102494.

[5] A. Furtado, R. F. Ramos, B. Maia, and J. M. Costa, "Predictors of Hotel Clients' Satisfaction in the Cape Verde Islands," *Sustain.*, vol. 14, no. 5, 2022, doi: 10.3390/su14052677.

[6] J. Park and B. K. Lee, "An opinion-driven decision-support framework for benchmarking hotel service," *Omega (United Kingdom)*, vol. 103, 2021, doi: 10.1016/j.omega.2021.102415.

[7] N. N. Arief and A. B. Pangestu, "Perception and Sentiment Analysis on Empathic Brand Initiative During the COVID-19 Pandemic: Indonesia Perspective," *J. Creat. Commun.*, vol. 17, no. 2, pp. 162–178, 2022, doi: 10.1177/09732586211031164.

[8] P. Rita, R. Ramos, M. T. Borges-Tiago, and D. Rodrigues, "Impact of the rating system on sentiment and tone of voice: A Booking.com and TripAdvisor comparison study," *Int. J. Hosp. Manag.*, vol. 104, no. 2, pp. 1–12, 2022, doi: 10.1016/j.ijhm.2022.103245.

[9] Y. Song, K. Liu, L. Guo, Z. Yang, and M. Jin, "Does hotel customer satisfaction change during the COVID-19? A perspective from online reviews," *J. Hosp. Tour. Manag.*, vol. 51, pp. 132–138, 2022, doi: 10.1016/j.jhtm.2022.02.027.

[10] Z. Gang and L. Chenglin, "Dynamic measurement and evaluation of hotel customer satisfaction through sentiment analysis on online reviews," *Journal of Organizational and End User Computing*, vol. 33, no. 6. 2021. doi: 10.4018/JOEUC.20211101.oa8.

[11] A. S. Oliveira, A. I. Renda, M. B. Correia, and N. Antonio, "Hotel customer segmentation and sentiment analysis through online reviews: An analysis of selected European markets," *Tour. Manag. Stud.*, vol. 18, no. 1, pp. 29–40, 2022, doi: 10.18089/tms.2022.180103.

[12] V. Chang, L. Liu, Q. Xu, T. Li, and C. H. Hsu, "An improved model for sentiment analysis on luxury hotel review," *Expert Systems*, vol. 40, no. 2. 2023. doi: 10.1111/exsy.12580.

[13] C. Zhang, Z. Xu, X. Gou, and S. Chen, "An online reviews-driven method for the prioritization of improvements in hotel services," *Tour. Manag.*, vol. 87, 2021, doi: 10.1016/j.tourman.2021.104382.

[14] F. Hu, H. Li, Y. Liu, and T. Teichert, "Optimizing service offerings using asymmetric impact-sentiment-performance analysis," *Int. J. Hosp. Manag.*, vol. 89, 2020, doi: 10.1016/j.ijhm.2020.102557.

[15] J. R. Saura, D. Palacios-Marques, and D. E. Ribeiro-Soriano, "Online Visitor'S Reviews and Their Influence on Sustainable Tourism Businesses: an Applied Analysis of User Generated Content," *Transform. Bus. Econ.*, vol. 22, no. 2, pp. 124–143, 2023, [Online]. Available: https://www.scopus.com/inward/record.uri?partnerID=HzOxMe3b&scp=85163606374&origin=inward

[16] R. Sann and P. C. Lai, "Understanding homophily of service failure within the hotel guest cycle: Applying NLP-aspect-based sentiment analysis to the hospitality industry," *Int. J. Hosp. Manag.*, vol. 91, 2020, doi: 10.1016/j.ijhm.2020.102678.

[17] O. Ozdemir, W. Han, and M. Dalbor, "Economic policy uncertainty and hotel occupancy: the mediating effect of consumer sentiment," *J. Hosp. Tour. Insights*, vol. 5, no. 2, pp. 253–273, Jan. 2022, doi: 10.1108/JHTI-08-2020-0149.

[18] K. Puh and M. Bagić Babac, "Predicting sentiment and rating of tourist reviews using machine learning," *J. Hosp. Tour.*

Journal of Information System Research (JOSH)
Volume 6, No. 2, Januari 2025, pp 857−868
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
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Insights, vol. 6, no. 3, pp. 1188–1204, Jan. 2023, doi: 10.1108/JHTI-02-2022-0078.
[19] N. Khamphakdee and P. Seresangtakul, "An Efficient Deep Learning for Thai Sentiment Analysis," *Data*, vol. 8, no. 5, 2023, doi: 10.3390/data8050090.
[20] A. Benlahbib and E. H. Nfaoui, "Aggregating customer review attributes for online reputation generation," *IEEE Access*, vol. 8, pp. 96550–96564, 2020, doi: 10.1109/ACCESS.2020.2996805.
[21] R. A. Hameed, W. J. Abed, and A. T. Sadiq, "Evaluation of Hotel Performance with Sentiment Analysis by Deep Learning Techniques," *Int. J. Interact. Mob. Technol.*, vol. 17, no. 9, pp. 70–87, 2023, doi: 10.3991/ijim.v17i09.38755.
[22] X. Guo, N. Zhao, and S. Cui, "Consumer reviews sentiment analysis based on CNN-BiLSTM," *Xitong Gongcheng Lilun yu Shijian/System Engineering Theory and Practice*, vol. 40, no. 3. pp. 653–663, 2020. doi: 10.12011/1000-6788-2018-1890-11.
[23] R. Xiang, E. Chersoni, Q. Lu, C. R. Huang, W. Li, and Y. Long, "Lexical data augmentation for sentiment analysis," *J. Assoc. Inf. Sci. Technol.*, vol. 72, no. 11, pp. 1432–1447, 2021, doi: 10.1002/asi.24493.
[24] A. Kathuria, A. Gupta, and R. K. Singla, "AOH-Senti: Aspect-Oriented Hybrid Approach to Sentiment Analysis of Students' Feedback," *SN Comput. Sci.*, vol. 4, no. 2, 2023, doi: 10.1007/s42979-022-01611-1.
[25] B. A. Smitha and R. K. N. Praveen, "ORDSAENet: Outlier Resilient Semantic Featured Deep Driven Sentiment Analysis Model for Education Domain," *J. Mach. Comput.*, vol. 3, no. 4, pp. 408–430, 2023, doi: 10.53759/7669/jmc202303034.
[26] Z. Al Faridzi, D. Pramesti, and R. Y. Fa'Rifah, "A Comparison of Oversampling and Undersampling Methods in Sentiment Analysis Regarding Indonesia Fuel Price Increase Using Support Vector Machine," *ICADEIS 2023 - International Conference on Advancement in Data Science, E-Learning and Information Systems: Data, Intelligent Systems, and the Applications for Human Life, Proceeding*. 2023. doi: 10.1109/ICADEIS58666.2023.10270851.
[27] A. Kulshrestha, V. Krishnaswamy, and M. Sharma, "Bayesian BILSTM approach for tourism demand forecasting," *Ann. Tour. Res.*, vol. 83, 2020, doi: 10.1016/j.annals.2020.102925.
[28] W. Li, L. Zhu, Y. Shi, K. Guo, and E. Cambria, "User reviews: Sentiment analysis using lexicon integrated two-channel CNN–LSTM family models," *Appl. Soft Comput. J.*, vol. 94, 2020, doi: 10.1016/j.asoc.2020.106435.
[29] F. Amali, H. Yigit, and Z. H. Kilimci, "Sentiment Analysis of Hotel Reviews using Deep Learning Approaches," *2024 IEEE Open Conference of Electrical, Electronic and Information Sciences, eStream 2024 - Proceedings*. 2024. doi: 10.1109/eStream61684.2024.10542593.
[30] Y. Du, Y. Wang, K. Wei, and J. Jia, "The Sentiment Analysis and Sentiment Orientation Prediction for Hotel Based on BERT-BiLSTM Model," *Lecture Notes in Electrical Engineering*, vol. 854 LNEE. pp. 498–505, 2022. doi: 10.1007/978-981-16-9423-3_62.
[31] S. Yang, X. Yu, and Y. Zhou, "LSTM and GRU Neural Network Performance Comparison Study: Taking Yelp Review Dataset as an Example," *Proceedings - 2020 International Workshop on Electronic Communication and Artificial Intelligence, IWECAI 2020*. pp. 98–101, 2020. doi: 10.1109/IWECAI50956.2020.00027.
[32] A. Sherstinsky, "Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network," *Phys. D Nonlinear Phenom.*, vol. 404, 2020, doi: 10.1016/j.physd.2019.132306.
[33] J. Q. Wang, Y. Du, and J. Wang, "LSTM based long-term energy consumption prediction with periodicity," *Energy*, vol. 197, 2020, doi: 10.1016/j.energy.2020.117197.
[34] H. Abbasimehr, M. Shabani, and M. Yousefi, "An optimized model using LSTM network for demand forecasting," *Comput. Ind. Eng.*, vol. 143, 2020, doi: 10.1016/j.cie.2020.106435.
[35] S. Kumar, "Deep learning based affective computing," *J. Enterp. Inf. Manag.*, vol. 34, no. 5, pp. 1551–1575, Jan. 2021, doi: 10.1108/JEIM-12-2020-0536.
[36] C. I. Eke, A. A. Norman, and L. Shuib, "Context-Based Feature Technique for Sarcasm Identification in Benchmark Datasets Using Deep Learning and BERT Model," *IEEE Access*, vol. 9, pp. 48501–48518, 2021, doi: 10.1109/ACCESS.2021.3068323.
[37] K. L. Tan, C. P. Lee, K. S. M. Anbananthen, and K. M. Lim, "RoBERTa-LSTM: A Hybrid Model for Sentiment Analysis With Transformer and Recurrent Neural Network," *IEEE Access*, vol. 10, pp. 21517–21525, 2022, doi: 10.1109/ACCESS.2022.3152828.
[38] S. Tam, R. Ben Said, and Ö. Tanriöver, "A ConvBiLSTM Deep Learning Model-Based Approach for Twitter Sentiment Classification," *IEEE Access*, vol. 9, pp. 41283–41293, 2021, doi: 10.1109/ACCESS.2021.3064830.
[39] Z. Ellaky, F. Benabbou, Y. Matrane, and S. Qaqa, "A Hybrid Deep Learning Architecture for Social Media Bots Detection Based on BiGRU-LSTM and GloVe Word Embedding," *IEEE Access*, vol. 12, pp. 100278–100294, 2024, doi: 10.1109/ACCESS.2024.3430859.
[40] U. Ependi, A. F. Rochim, and A. Wibowo, "A Hybrid Sampling Approach for Improving the Classification of Imbalanced Data Using ROS and NCL Methods," *Int. J. Intell. Eng. Syst.*, vol. 16, no. 3, pp. 345–361, 2023, doi: 10.22266/ijies2023.0630.28.
[41] I. Aruleba and Y. Sun, "Effective Credit Risk Prediction Using Ensemble Classifiers With Model Explanation," *IEEE Access*, vol. 12, pp. 115015–115025, 2024, doi: 10.1109/ACCESS.2024.3445308.
[42] R. Cai *et al.*, "Sentiment analysis about investors and consumers in energy market based on BERT-BILSTM," *IEEE Access*, vol. 8, pp. 171408–171415, 2020, doi: 10.1109/ACCESS.2020.3024750.
[43] H. Kim, K. K. F. So, S. Shin, and J. Li, "Artificial Intelligence in Hospitality and Tourism: Insights From Industry Practices, Research Literature, and Expert Opinions," *J. Hosp. Tour. Res.*, 2024, doi: 10.1177/10963480241229235.
[44] L. Solomovich and V. Abraham, "Exploring the influence of ChatGPT on tourism behavior using the technology acceptance model," *Tour. Rev.*, 2024, doi: 10.1108/TR-10-2023-0697.
[45] R. A. Rather, "AI-powered ChatGPT in the hospitality and tourism industry: benefits, challenges, theoretical framework, propositions and future research directions," *Tourism Recreation Research*. 2024. doi: 10.1080/02508281.2023.2287799.
[46] H. S. Saragih, M. R. U. Saputra, and M. H. Dewantara, "Exploring Topics and Trends in Service Robots, Artificial Intelligence, and Realities in Tourism: A Text-Mining Approach," *Emerging Technologies in Business*. pp. 239–259, 2024. doi: 10.1007/978-981-97-2211-2_11.
[47] A. E. Sousa, P. Cardoso, and F. Dias, "The Use of Artificial Intelligence Systems in Tourism and Hospitality: The

Journal of Information System Research (JOSH)
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DOI 10.47065/josh.v6i2.6420

Tourists' Perspective," *Adm. Sci.*, vol. 14, no. 8, 2024, doi: 10.3390/admsci14080165.
[48] Z. Altinay, F. Altinay, A. Tlili, and S. Vatankhah, "'Keep your friends close, but your enemies closer:' ChatGPT in tourism and hospitality," *J. Hosp. Tour. Technol.*, 2024, doi: 10.1108/JHTT-03-2024-0139.
[49] J. Zhang, D. J. Mills, and H. W. Huang, "Enhancing Travel Planning and Experiences with Multimodal ChatGPT 4.0," *ACM International Conference Proceeding Series*. pp. 12–19, 2024. doi: 10.1145/3655497.3655529.
[50] F. Folino, T. Ruga, E. Zumpano, and E. Vocaturo, "Visualizing Tourism's Future: The Impact of Image-Based AI on Destination Development," *2024 IEEE International Workshop on Metrology for Living Environment, MetroLivEnv 2024 - Proceedings*. pp. 81–86, 2024. doi: 10.1109/MetroLivEnv60384.2024.10615477.