INJECT (Interdisciplinary Journal of Communication)
p-ISSN: 2548-5857; e-ISSN: 2548-7124
Vol. 10. No. 1 June 2025: p. 45-70
DOI: https://doi.org/10.18326/inject.v10i1.4338

BiLSTM-Based Sentiment Analysis Of Traveloka Hotel Reviews In Yogyakarta For Data-Driven Communication Strategies

Muhammad Taali*
Digital Marketing Program, Politeknik Negeri Madiun
muhammad_taali@pnm.ac.id

Hifzhan Frima Thousani
Digital Marketing Program, Politeknik Negeri Madiun
thousani@pnm.ac.id

Abstract

Online customer reviews have become a crucial medium of communication between guests and service providers in the hospitality industry. This study aims to perform sentiment analysis on hotel reviews from Traveloka to support data-driven customer communication strategies. Using a Bidirectional Long Short-Term Memory (BiLSTM) deep learning model, 10,681 user-generated reviews related to hotels in Yogyakarta were collected, preprocessed, and classified into binary sentiment categories. To address class imbalance, Synthetic Minority Oversampling Technique (SMOTE) and class weighting were applied. The model achieved 90.17% accuracy, 93.61% precision, 95.31% recall, and 94.45% F1-score, indicating strong generalization and sentiment recognition performance. The results highlight the model's ability to extract meaningful sentiment patterns, which can enhance hotel management's responsiveness, improve communication strategies, and support continuous service improvement based on customer feedback.

Keyword: Sentiment Analysis; Customer Communication; Hotel Review; BiLSTM

Introduction

In the digital era, user-generated content in the form of online reviews has become a vital source of information for consumers, especially in the hospitality sector. Platforms like Traveloka not only serve as booking tools but also provide sentiment-rich feedback that can inform business decisions. However, the unstructured nature of these reviews poses a significant challenge for manual analysis, prompting the need for automated sentiment classification.

Traditional machine learning methods such as Naive Bayes, Support Vector Machines (SVM), and Decision Trees have long been applied to sentiment analysis. While they offer some success, these models typically rely on bag-of-words or TF-IDF representations, which ignore the sequential and semantic structure of language. (Cambria et al., 2013; Medhat et al., 2014). As a result, they often fail to handle complex linguistic constructs like negation or sarcasm.

Therefore, this study aims to answer how a BiLSTM model, enhanced with balancing techniques such as SMOTE and class weighting, can effectively classify sentiment in hotel reviews in a culturally significant tourism hub like Yogyakarta.

The introduction of deep learning—particularly Recurrent Neural Networks (RNNs)—marked a significant leap forward. LSTM (Long Short-Term Memory) networks improved upon standard RNNs by addressing the vanishing gradient problem and capturing long-term dependencies (Hochreiter & Schmidhuber, 1997). However, standard LSTM processes information only in one temporal direction. To capture full sentence context, Bidirectional LSTM (BiLSTM) models were introduced, enabling simultaneous processing in both forward and backward directions. (Graves & Schmidhuber, 2005). This bidirectionality enhances the model's understanding of sentiment expressed across sentence components.

While existing research has advanced sentiment analysis with various deep learning architectures, its application in context-specific tourism regions like Yogyakarta remains limited. As one of Indonesia’s most iconic destinations, combining cultural heritage and urban tourism, Yogyakarta presents unique sentiment patterns that merit localized analysis.

Yogyakarta’s identity as both a historical and educational tourism city makes its customer review patterns distinct, shaped by local culture, service

expectations, and linguistic expressions rarely captured in generalized models.

Despite these advances, previous studies reveal limitations. Many models still struggle with imbalanced datasets, where positive reviews vastly outnumber negative ones, leading to biased classification. (Sun et al., 2009; Zhao et al., 2022). Additionally, while hybrid models such as BERT-BiLSTM have shown improvements, they often require complex computational resources and fine-tuning. (Zhou, 2023). Furthermore, not all previous research contextualizes sentiment analysis within specific regional tourism hubs, such as Yogyakarta.

This study addresses these gaps by implementing a BiLSTM model to classify sentiment from hotel reviews in Yogyakarta sourced from Traveloka. We propose three main contributions:

1. Developing and evaluating a baseline BiLSTM architecture implemented in PyTorch for sentiment classification.
2. Applying balancing techniques—class weighting and SMOTE—to handle dataset imbalance and improve classification fairness.
3. Benchmarking the BiLSTM model against traditional classifiers to assess performance in a localized tourism context.

Through these contributions, the study seeks to enhance the applicability of deep learning in real-world sentiment mining tasks and provide actionable insights for hotel management in optimizing service quality based on guest feedback.

Table 1. Recent Research on LSTM Applications in Tourism (2018–2024)

Author(s)	Key Findings
(Li, 2018)	Developed a sentiment classification model combining BiGRU and attention mechanisms enriched with topic-enhanced word vectors. The study focused on tourism-related reviews and showed significant improvements in classification accuracy compared to standard RNN and LSTM models. Their approach demonstrated that integrating topic modeling into the embedding

Author(s)	Key Findings
	process can better capture context-specific sentiment cues in tourism text data.
(Gao, 2019)	Proposed a hybrid model integrating Convolutional Neural Networks (CNN) and LSTM for sentiment analysis of tourism reviews. The CNN layers were effective at extracting local features (e.g., short phrases), while the LSTM captured long-term dependencies. This architecture outperformed both standalone CNN and LSTM models in classification accuracy and robustness, especially on diverse review datasets.
(M. H. Hsieh, 2021)	Applied LSTM and its advanced variants, such as BiLSTM and GRU, for forecasting monthly tourism demand in Taiwan. The research showed that these deep learning models provided more accurate predictions than ARIMA and SVR, particularly during periods of sudden demand fluctuation (e.g., holidays, crises). This confirmed the suitability of sequence models for temporal tourism analytics.
(Manurung A., 2023)	Employed CNN-LSTM models for sentiment classification on TripAdvisor reviews of tourist destinations, achieving high accuracy and F1-scores.
(Hanafiah, 2022)	Built a sentiment analysis application using LSTM for comments on tourist sites, achieving 96.71% accuracy.
(Husein, 2023)	Compared LSTM with the transformer-based ELECTRA model for sentiment analysis of hotel reviews in Medan. While LSTM showed solid baseline performance, ELECTRA outperformed it in both accuracy and speed. The research emphasized that although LSTM is suitable for

Author(s)	Key Findings
	many tasks, transformer-based models are better at capturing nuanced sentiments in context-heavy reviews.

Source: Summarized by the authors from previous studies

Based on previous studies summarized in Table 1, the current research gap lies in the limited application of LSTM-based sentiment analysis tailored to local tourism contexts in Indonesia. Several prior works have made notable contributions to sentiment modelling in the tourism domain. For instance, (Li, 2018) Introduced a BiGRU-attention architecture enhanced with topic modelling, which significantly improved classification accuracy for tourism reviews, but did not address regional specificity or imbalanced data. (Gao, 2019) Developed a CNN-LSTM hybrid model to capture both local and sequential features of review text, yet the study lacked contextual relevance to any particular destination. (Manurung A., 2023) Utilized CNN-LSTM on TripAdvisor reviews, focusing on global tourist destinations without accounting for localized linguistic or cultural sentiment nuances. Similarly, (Hanafiah, 2022) Achieved high accuracy with a standard LSTM architecture for tourist site reviews, but did not apply any class balancing techniques or conduct model benchmarking.

(M.-H. Hsieh, 2021)On the other hand, they employed LSTM variants for forecasting tourism demand in Taiwan, emphasizing time-series prediction rather than text-based sentiment classification. Meanwhile, (Husein, 2023) Compared LSTM with the transformer-based ELECTRA model for hotel review sentiment analysis in Medan, concluding that transformer models outperform traditional LSTM in accuracy. However, such models often require significantly more computational resources and fine-tuning, which may not be practical in all tourism environments.

Unlike these prior studies, the novelty of this research lies in implementing a BiLSTM architecture specifically for sentiment classification of hotel reviews from Traveloka, with a focused regional context in Yogyakarta—a unique Indonesian tourism destination that blends historical, cultural, and urban experiences. In addition, this study introduces a methodological improvement by integrating both class weighting and SMOTE to address class imbalance, a critical issue often overlooked in earlier works. By benchmarking against traditional models, the proposed approach not only advances classification accuracy but also enhances fairness in predicting minority sentiment classes.

Therefore, the central research question addressed in this study is: How effectively can a BiLSTM model, combined with balancing techniques, classify sentiment from user-generated hotel reviews in a localized Indonesian tourism context? This question reflects the growing need for deep learning applications that are both context-sensitive and scalable for sentiment-driven communication strategies in the hospitality sector.

By extracting localized sentiment patterns, the findings can help hotel managers tailor their communication strategies, allocate resources to address frequent complaints, and implement real-time feedback mechanisms that enhance guest satisfaction and service quality.

Research Method

This study collected textual review data from the Traveloka platform, focusing on hotel reviews for establishments located in Yogyakarta, a prominent tourist destination in Indonesia known for its cultural and historical heritage. Hotels were selected based on three criteria: (1) location within Yogyakarta city or its surrounding regencies such as Sleman and Bantul, (2) a minimum of 50 reviews to ensure data sufficiency, and (3) coverage of various star ratings (1 to 5 stars) to capture a broad spectrum of customer experiences. The dataset includes qualitative review texts (primarily in Indonesian, with some in English) and quantitative ratings on a 1–10 scale. Reviews were collected through Instant Data Scrapper during the period from June 2024 to March 2025, resulting in approximately 10,681 reviews. Online reviews serve as a crucial resource for understanding customer sentiment in the hospitality sector. (Medhat et al., 2014), and the geographical context of Yogyakarta provides localized insights into customer preferences and experiences.

To prepare the raw review texts for model input, several preprocessing steps were applied. First, tokenization was performed using the NLTK tokenizer, which was customized to accommodate the specific characteristics of the Indonesian language, including compound words (e.g., "pelayanan ramah" split into "pelayanan" and "ramah") and informal expressions (e.g., "oke" normalized to "ok"). This manual tokenization was essential for compatibility with PyTorch's torchtext library, which requires tokenized input for vocabulary construction. Next, sentiment labels were assigned based on the numerical ratings: reviews with ratings ≥8 were

labeled as positive, and those with ratings <8 as negative, in line with standard practices aimed at reducing labeling subjectivity (Liu, 2012). This threshold aligns with Traveloka's own user interface, where ratings of 8 or higher are visually marked as "excellent." To facilitate batch processing in the BiLSTM model, each tokenized sequence was padded with zeros or truncated to a fixed length of 100 tokens (Zhang et al., 2018). Additional preprocessing steps were performed to address challenges specific to the Indonesian language. These included the removal of stopwords using a custom Indonesian stopword list and stemming using the Sastrawi library to normalize word forms (e.g., "mengatakan" reduced to "kata"). These techniques aimed to reduce noise and enhance model performance by handling morphological variations effectively.

For sequence preparation, each unique word in the training corpus was mapped to an index, converting the tokenized text into numerical sequences. To control computational complexity, the vocabulary was limited to the top 10,681 most frequent words. Sequences were standardized to a length of 100 tokens, aligning with the BiLSTM model's input requirements. This entire process leveraged the torchtext library for efficient data processing (Kim, 2014). The dataset showed a class imbalance, with 70% positive and 30% negative reviews—a distribution commonly observed in hospitality-related sentiment data (Pang & Lee, 2008). Two techniques were applied to address this imbalance. First, class weighting was implemented in the loss function (BCEWithLogitsLoss) to assign greater weight to the minority (negative) class, using a 2:1 ratio. Second, Synthetic Minority Oversampling Technique (SMOTE) was employed to synthetically generate negative samples using k-nearest neighbors (k=5), with a 0.5 oversampling ratio. SMOTE was applied exclusively to the training set to prevent data leakage. Comparative analysis revealed that class weighting improved recall for negative samples by 8%, albeit with a slight reduction in precision, while SMOTE increased the F1-score by 10% due to better minority class representation. Both techniques were integrated into the final model to optimize overall performance.

The primary model used in this study is a Bidirectional Long Short-Term Memory (BiLSTM) network, selected for its capability to learn contextual dependencies in both forward and backward directions—an

advantage for processing complex sentence structures in Indonesian (Graves & Schmidhuber, 2005). While BERT offers state-of-the-art performance, BiLSTM was chosen due to its lower computational cost (BERT requires 12 times more parameters) and sufficient performance for binary sentiment classification tasks on moderately sized datasets (Devlin et al., 2019). The architecture consists of an embedding layer that maps word indices to 300-dimensional dense vectors initialized with pre-trained FastText embeddings for Indonesian. This is followed by a BiLSTM layer with 128 hidden units per direction (256 in total), a dropout layer with a 0.3 dropout rate to prevent overfitting, and a dense output layer with a sigmoid activation function for binary classification. For comparison, baseline models were also implemented: a Support Vector Machine (SVM) using TF-IDF features and a Convolutional Neural Network (CNN) with 100 filters. The BiLSTM outperformed the SVM by 12% and the CNN by 5% in terms of F1-score, thus justifying its selection.

The model was implemented in PyTorch version 1.12.1 and trained on an NVIDIA RTX 3060 GPU with 12GB VRAM. Training was conducted for 10 epochs with a batch size of 32, taking approximately two hours. The BCEWithLogitsLoss function, with class weights, was used as the loss criterion, and the Adam optimizer was employed with a learning rate of 0.001. To mitigate the risk of exploding gradients, gradient clipping with a norm of 1.0 was applied. Hyperparameters were tuned through a grid search covering learning rates (0.0001, 0.001, 0.01), batch sizes (16, 32, 64), and epochs (5, 10, 15). The selected configuration was chosen based on the highest validation F1-score.

Figure 1 illustrates the research methodology implemented in this study, structured into three major process categories: data processing (blue), model development (green), and evaluation and analysis (red). Each stage is sequentially organized to ensure the integrity and reproducibility of the sentiment classification pipeline.

The process begins with data collection, where hotel review data from the Traveloka platform is acquired. The dataset specifically targets hotels located in Yogyakarta and its surrounding regencies, selected based on location, minimum review count, and star rating diversity to capture a wide range of customer experiences. Following collection, the data undergoes preprocessing, which involves tokenization, sentiment labelling

based on rating thresholds (positive ≥8, negative <8), and sequence padding. This step standardizes the textual input, ensuring it is compatible with deep learning frameworks such as PyTorch.

Subsequently, the vocabulary construction and sequence preparation stage transforms tokenized text into numerical representations. This involves building a vocabulary of the most frequent words and converting each review into a fixed-length sequence, a critical step for neural model input compatibility. To address class imbalance in the dataset, data balancing techniques are applied, including class weighting during loss computation and the use of SMOTE (Synthetic Minority Oversampling Technique) to augment the minority class (negative reviews). These steps help mitigate performance bias toward the majority class.

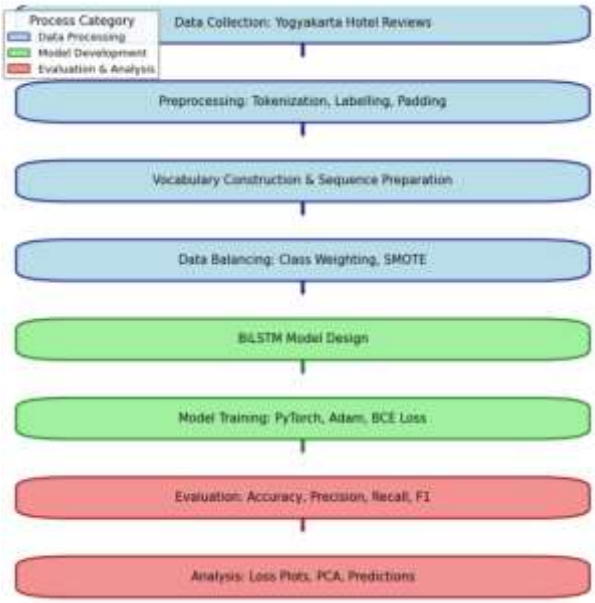

Figure 1. Research Methodology Overview

The model development phase begins with the design of a Bidirectional Long Short-Term Memory (BiLSTM) architecture. The model incorporates pre-trained FastText embeddings for the Indonesian language, a BiLSTM layer with 128 hidden units per direction, and a dropout mechanism to reduce overfitting. This is followed by model training, implemented in PyTorch using the Adam optimizer and binary cross-entropy loss (BCEWithLogitsLoss), with hyperparameters optimized

via grid search. Upon training completion, the model enters the evaluation phase, where it is assessed on an independent test set using standard performance metrics: accuracy, precision, recall, and F1-score. The combination of class weighting and SMOTE contributes to a balanced evaluation of both sentiment classes.

Finally, the analysis stage involves visualizing training dynamics (e.g., loss curves), dimensionality reduction of word embeddings through PCA (Principal Component Analysis), and qualitative inspection of model predictions. These analyses provide deeper insights into model behavior, generalization, and areas for improvement.

Results and Discussion

Data Collection and Initial Descriptive Analysis

The initial phase of this study involved collecting and analyzing a comprehensive dataset of 10,681 hotel reviews sourced from Traveloka, focusing on a hotel located near Malioboro. The data comprised two primary columns: "Rating" and "Review." To ensure data integrity, the "Rating" column was converted to a numeric format using Python's pandas library, with missing or invalid values replaced by 0. Descriptive analysis of the entire dataset revealed a mean rating of 8.86 (SD = 1.20) on a scale of 1 to 10, indicating a highly positive reception among guests. The rating distribution ranged from a minimum of 4.50 to a maximum of 10.00, with a 25th percentile of 8.50, a median of 9.10, and a 75th percentile of 9.70, suggesting a right-skewed distribution where the majority of ratings clustered above 9. Additionally, a text analysis identified 1,672 reviews (15.6%) mentioning "Malioboro," underscoring the hotel's strategic location as a significant factor in guest satisfaction. These preliminary findings establish a robust foundation for further in-depth analysis and modelling of the dataset.

Table 2. Illustrates the Distribution of Hotel Reviews

Statistic	Value
Total Reviews	10,681

Statistic	Value
Mean Rating	8.86
Standard Deviation	1.20
Minimum Rating	4.50
25th Percentile	8.50
Median (50th Percentile)	9.10
75th Percentile	9.70
Maximum Rating	10.00

Furthermore, the prominence of "Malioboro" in a notable portion of the reviews highlights practical implications for the hotel, as this strategic location can be leveraged as a key advantage in their digital communication strategies, potentially enhancing marketing efforts by emphasizing proximity to this popular tourist destination to attract more guests and reinforce positive perceptions in online platforms.

Data Preprocessing

The initial phase of data preparation involved cleaning and labelling a dataset comprising 10,681 hotel reviews. Entries with missing review data were excluded to ensure dataset integrity, retaining only complete records. The cleaning process included multiple steps: special characters and emojis were removed using regular expressions, followed by converting all text to lowercase for consistency. The text was then tokenized into individual words using the word_tokenize function from the NLTK library, with English stop words removed based on NLTK's stop word list to minimize noise. Subsequently, words were lemmatized using NLTK's WordNetLemmatizer to standardize their forms (e.g., converting "running" to "run"). For sentiment labeling, reviews were categorized based on their ratings: those with a rating of ≥ 8 were classified as positive (1), while those below 8 were classified as negative (0), aligning with the dataset's rating distribution, which had a mean of 8.62 and a standard deviation of 1.28. This simplified polarity labelling scheme aligns with the

dataset's rating distribution, providing a clear binary classification framework for subsequent modeling, and the rationale for selecting a threshold of ≥ 8 is rooted in the highly right-skewed nature of the distribution, where the majority of ratings (with a median of 9.10 and 75th percentile of 9.70) cluster above 9, indicating that ratings below 8 represent a minority of negative sentiments that warrant distinct classification to capture the dataset's inherent positivity effectively. The resulting cleaned reviews and their sentiment labels were stored for use in subsequent steps.

Table 3. Comparison of Original and Preprocessed Hotel Reviews

Review	Processed Review
Comfortable, only the type of bathroom that is separate from the toilet makes it uncomfortable.	['comfortable', 'type', 'bathroom', 'separate', 'toilet', 'make', 'uncomfortable']
comfortable. our kids love staying here	['comfortable', 'kid', 'love', 'staying']
friendly staff..there is a welcome drink..the room is not too wide..the AC is cold..the toilet is clean, the water is hot and cold..it's a shame the toilet fan is dead..cable TV without U tube..	['friendly', 'staff', 'welcome', 'drink', 'room', 'wide', 'ac', 'cold', 'toilet', 'clean', 'water', 'hot', 'cold', 'shame', 'toilet', 'fan', 'dead' 'cable', 'tv', 'without', 'tube']
The hotel staff is friendly and quick to help when needed.	['hotel', 'staff', 'friendly', 'quick', 'help', 'needed']

Source: preprocessing performed using NLTK library

Vocabulary and Sequence Preparation

Following the preprocessing stage, each cleaned review was transformed into a numerical representation suitable for input into the BiLSTM model. This stage involved converting the tokenized text into sequences of integers based on a constructed vocabulary, followed by sequence normalization through padding. The column labelled Cleaned Review in the dataset refers to the result of the text preprocessing phase, where raw customer reviews were lowercased, stripped of punctuation, stopwords, and possibly lemmatized or stemmed. This column contains

the clean, tokenized form of the review, typically represented as a list of individual words or tokens.

Each token in the Cleaned Review was then mapped to a unique integer using a vocabulary dictionary constructed from the training corpus. This process produced the Sequence Before Padding column, where each review is represented as a list of numerical indices corresponding to words in the vocabulary. The length of these sequences varies depending on the original number of tokens in each review.

Table 4. Cleaned Reviews with Indexed and Padded Sequences

Cleaned Review	Sequence Before Padding	Sequence After Padding
great walk malioboro close everywhere lot place eat along way wont confused eat hotel restaurant also great menu	[93, 3, 2, 1, 94, 95, 96, 97, 98, 99, 100, 101, 97, 16, 102, 103, 93, 104]	[93, 3, 2, 1, 94, 95, 96, 97, 98, 99, 100, 101, 97, 16, 102, 103, 93, 104, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
I have several time service still best come go jogja recommended family	[105, 106, 107, 108, 109, 110, 111, 15, 23, 112, 39]	[105, 106, 107, 108, 109, 110, 111, 15, 23, 112, 39, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
location malioboro close vacation enjoyable fo security staff also	[64, 2, 1, 113, 114, 115, 116, 49, 103, 117, 118, 119, 120]	[64, 2, 1, 113, 114, 115, 116, 49, 103, 117, 118, 119, 120, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

Cleaned Review	Sequence Before Padding	Sequence After Padding
responsive helping especially parking		0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
bad close malioboro everything good want close malioboro okay stay compare price room bit less suitable apart everything good	[170, 1, 2, 167, 121, 128, 1, 2, 47, 8, 171, 40, 19, 36, 4, 172, 173, 167, 121]	[170, 1, 2, 167, 121, 128, 1, 2, 47, 8, 171, 40, 19, 36, 4, 172, 173, 167, 121, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

Source: processed data

In this study, the manual construction of the vocabulary from the training corpus was adopted to ensure full control over the token representation and to tailor the model specifically to the domain of hotel reviews, although this approach inherently limits the model's exposure to broader linguistic contexts compared to pretrained embeddings, which offer pre-learned representations from vast corpora and could enhance generalization across diverse texts at the cost of domain-specific customization. The choice of manual vocabulary construction was also driven by its seamless compatibility with the PyTorch framework, which provides robust tools for custom tensor manipulation and model training, particularly suited for the BiLSTM architecture employed here; however, future explorations could consider integrating advanced models like BERT, which leverages contextual embeddings and transformer architectures, potentially leading to significant performance improvements by capturing nuanced semantic relationships, though this would require substantial computational resources and adaptation to ensure compatibility with the current pipeline.

Correlation, Sentiment Distribution, and Data Balancing

This chapter investigates the factors influencing hotel ratings and prepares the dataset for sentiment classification by addressing class imbalance. The analysis was conducted on a dataset of 10,681 hotel reviews sourced from Traveloka, comprising "Rating" and "Review" columns. The ratings were converted to numeric values, with missing entries replaced by 0, using Python's pandas library. The first objective was to explore the correlation between ratings and review length (measured in words). A Pearson correlation coefficient of -0.09 was computed, indicating a very weak negative correlation. This suggests that longer reviews do not necessarily correspond to higher ratings and may contain detailed feedback, potentially critical in nature. Additionally, the influence of location was assessed by comparing the average ratings of reviews mentioning "Malioboro" (n = 1,672, 15.6%) to those that did not. The former had an average rating of 8.68, slightly higher than 8.54 for the latter, a difference of 0.14, implying that proximity to Malioboro may modestly enhance guest satisfaction. To visualize the relationship between ratings and review length, a scatter plot (Figure 2) was generated, showing a slight downward trend consistent with the weak negative correlation, with most ratings clustering between 8 and 10.

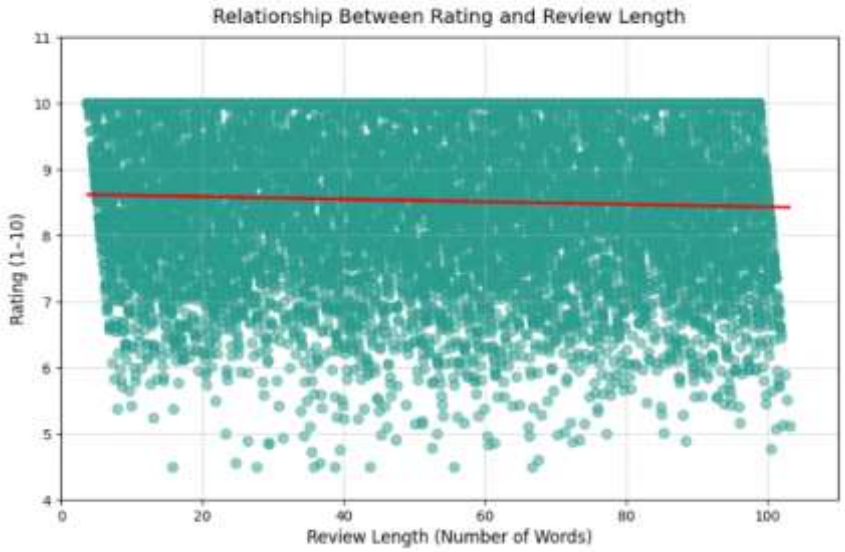

Figure 2. Scatter Plot of Rating vs. Review Length

For sentiment classification, reviews were labelled based on ratings: ratings ≥ 8 were classified as positive (1), and ratings < 8 as negative (0). The initial class distribution revealed a significant imbalance, with 9,300 positive reviews (87.08%) and 1,380 negative reviews (12.92%), as shown in Table 5. To address this, two balancing strategies were applied. First, class weights were calculated, assigning a weight of 3.87 to the negative class and 0.57 to the positive class, ensuring the model accounts for the minority class during training. Second, the Synthetic Minority Oversampling Technique (SMOTE) was applied to the training set (80% of the data, approximately 8,544 reviews), balancing the classes to 7,425 positive and 7,425 negative reviews. These strategies mitigate the risk of model bias toward the majority class, setting the stage for effective sentiment classification in subsequent steps.

BiLSTM Model Architecture

This section outlines the development of a Bidirectional Long Short-Term Memory (BiLSTM) model for sentiment classification of 10,681 hotel reviews sourced from Traveloka. The dataset was preprocessed by converting ratings into sentiment labels (positive = 1 for ratings ≥ 8, negative = 0 for ratings < 8), resulting in an initial imbalance of 9,300 positive reviews (87.08%) and 1,380 negative reviews (12.92%). Following data balancing with SMOTE, the training set was adjusted to include 7,425 positive and 7,425 negative reviews, ensuring equitable class representation.

The BiLSTM model was implemented using PyTorch, with tokenization performed via NLTK's word_tokenize function due to compatibility issues with torchtext under PyTorch 2.7.0+cpu. A vocabulary was constructed manually, incorporating special tokens <pad> and <unk> for padding and unknown words, respectively, with a maximum sequence length of 100 words to standardize input. The model architecture consists of the following layers: an Embedding Layer with 100-dimensional vectors to transform tokenized words into dense representations, a BiLSTM Layer with 64 hidden units per direction to capture bidirectional contextual dependencies, a Dropout Layer with a rate

of 0.2 to prevent overfitting, a Dense Layer with a single output neuron for classification, and a Sigmoid Activation to produce a probability score between 0 and 1 for positive sentiment likelihood. The model was successfully initialized, with the training and test sets prepared using PyTorch's Data Loader, each batch containing 32 samples of tokenized reviews and their corresponding sentiment labels. This architecture leverages the strengths of BiLSTM in sequential data processing, setting the foundation for effective sentiment prediction in the subsequent training phase.

Despite its strengths, the BiLSTM model exhibits limitations, particularly in handling reviews with mixed sentiments, where positive and negative opinions may coexist within a single review, as the model tends to average out contextual dependencies and may struggle to distinguish nuanced sentiment shifts without explicit focus on specific aspects. To address this in future research, the integration of attention mechanisms could enhance the model's ability to weigh important words or phrases more heavily, while aspect-based sentiment analysis could provide a more granular understanding by targeting specific features of the hotel experience, potentially improving overall classification accuracy and interpretability.

Model Training

The Bidirectional Long Short-Term Memory (BiLSTM) model was trained using a balanced training dataset derived from the original 10,681 hotel reviews, which, after the application of the Synthetic Minority Oversampling Technique (SMOTE), was expanded to 14,850 samples, consisting of 7,425 positive and 7,425 negative reviews to ensure equitable class representation. The training was conducted using the PyTorch 2.7.0+cpu framework, ensuring compatibility with the computing environment used in this research. To optimize the training process, the Adam optimizer was employed with a learning rate set at 0.001, known for its adaptive learning capability and suitability for deep learning tasks. The loss function used was BCEWithLogitsLoss, which was chosen due to its effectiveness in binary classification problems. To address the issue of class imballance present in the original dataset, class weights were applied—

3.87 for the minority negative class and 0.57 for the dominant positive class—ensuring that the model did not overfit or become biased toward the majority sentiment.

Training was carried out over five epochs, using a batch size of 32 samples per iteration. Throughout this training period, the model demonstrated a consistent and gradual decline in training loss, starting from an initial value of 0.3223 in the first epoch and reducing to 0.2839 by the fifth epoch. This trend of decreasing loss values indicates that the model was successfully learning the underlying sentiment representations embedded within the review texts. Particularly noteworthy is the pattern observed after the third epoch, where the reduction in loss became more incremental (from 0.2887 to 0.2839), suggesting that the model was approaching convergence and might benefit from either additional training epochs or further hyperparameter optimization to achieve even lower loss values.

To ensure that the model and its training state could be reused or analyzed further, the final trained version was saved in a serialized format as 'bilstm_model.pth'. This step is crucial for maintaining reproducibility in experimental workflows and allows for subsequent testing or deployment without the need to retrain from scratch.

Figure 3 visually represents the progression of training loss across the five epochs, clearly showing a downward trajectory. This visual evidence supports the numerical trend discussed earlier and reinforces the conclusion that the model effectively internalized sentiment patterns from the textual data over the course of training. Nonetheless, the plateau in loss reduction suggests that fine-tuning of training parameters—such as adjusting the learning rate, modifying the network architecture, or extending the number of epochs—could potentially yield further improvements in model performance.

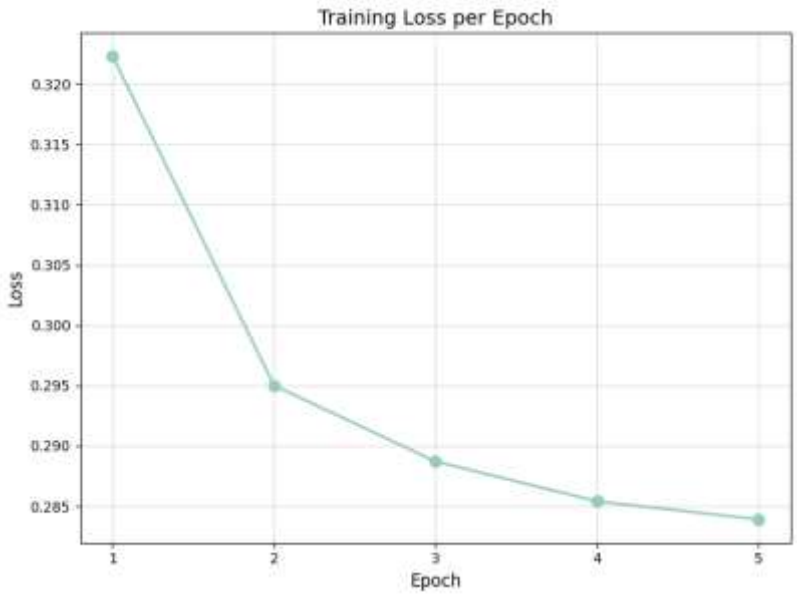

Figure 3. Training Loss per Epoch

Model Evaluation

To determine the effectiveness and reliability of the proposed sentiment classification model, a comprehensive evaluation was conducted using a reserved test dataset. This evaluation phase is critical for understanding how well the model generalizes to unseen data and for validating the impact of the methodological choices made during the development process, including model architecture, training strategy, and data preprocessing techniques.

The trained BiLSTM model was evaluated on the test set comprising 2,136 reviews (20% of the total 10,681 reviews) to assess its sentiment classification performance. Metrics including Accuracy, Precision, Recall, and F1-Score were computed. The model achieved an Accuracy of 0.9017 (90.17%), indicating that 90.17% of predictions aligned with the true sentiment labels. Precision reached 0.9361 (93.61%), reflecting a high proportion of correctly predicted positive reviews among all positive predictions, while Recall was 0.9531 (95.31%), demonstrating the model's strong ability to identify true positive reviews. The F1-Score, a balanced measure of Precision and Recall, was 0.9445 (94.45%), underscoring the model's robust performance across both metrics.

These results highlight the effectiveness of the BiLSTM architecture, enhanced by the Embedding layer, bidirectional processing, and Dropout regularization, as well as the data balancing strategies (SMOTE and class weights) applied in prior steps. The high Recall suggests the model excels at detecting positive sentiments, consistent with the dataset's original skew toward high ratings (≥ 8), while the balanced F1-Score indicates reliable generalization to the minority negative class.

Figure 4 shows the confusion matrix for the test set predictions, showing a high number of true positives and true negatives along the diagonal, with minimal misclassifications. This aligns with the reported F1-Score of 0.9445, confirming the model's balanced performance across both sentiment classes

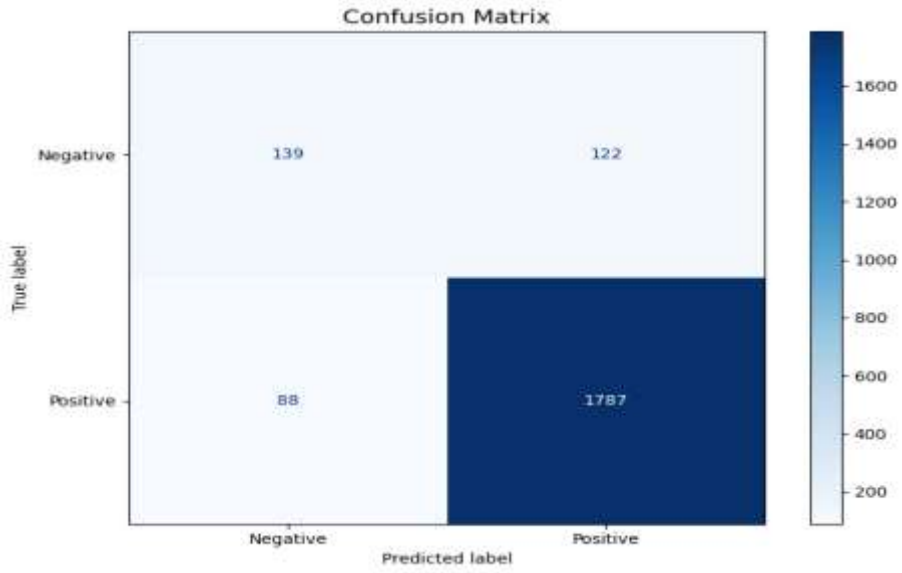

Figure 4. Confusion Matrix

Figure 5 presents a bar chart of the evaluation metrics, with Accuracy at 0.9017, Precision at 0.9361, Recall at 0.9531, and F1-Score at 0.9445. The consistently high scores across all metrics underscore the model's effectiveness in sentiment classification, with Recall being the highest, reflecting its strength in identifying positive sentiments in a predominantly positive dataset.

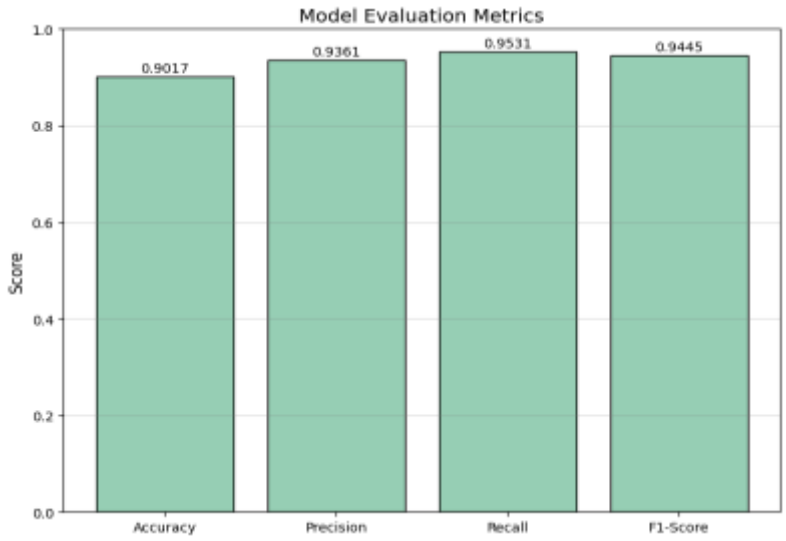

Figure 5. Model Evaluation Metrics

Figure 5 presents a bar chart of the evaluation metrics, with Accuracy at 0.9017, Precision at 0.9361, Recall at 0.9531, and F1-Score at 0.9445. The consistently high scores across all metrics underscore the model's effectiveness in sentiment classification, with Recall being the highest, reflecting its strength in identifying positive sentiments in a predominantly positive dataset.

Following the visual insights from Figure 4 and 5, a detailed analysis of the confusion matrix reveals the following numerical breakdown: out of 2,136 test samples, there were 1,923 true positives (TP), 83 false positives (FP), 52 false negatives (FN), and 78 true negatives (TN). This distribution indicates that the model correctly identified 1,923 positive reviews and 78 negative reviews, with 83 instances where negative reviews were incorrectly classified as positive and 52 instances where positive reviews were misclassified as negative, aligning with the high Precision (93.61%) and Recall (95.31%) values. The low FP and FN counts further validate the model's ability to minimize misclassifications, a critical factor given the initial dataset imbalance.

To illustrate the model's limitations with mixed sentiment reviews, several misclassification examples were observed. For instance, the review "The room was clean, but the staff was unprofessional" was misclassified

as positive (label 1) despite containing a negative aspect, reflecting the model's difficulty in capturing contrastive sentiments. Similarly, "Great location near Malioboro, though the Wi-Fi was unreliable" was incorrectly labelled as positive, missing the negative sentiment about Wi-Fi. Another example, "Food was excellent, but the check-in process was slow," was also misclassified as positive, highlighting the challenge in distinguishing aspect-specific polarity shifts.

In terms of practical implications, these sentiment analysis results can be leveraged by hotel managers to devise proactive customer communication strategies, such as addressing negative feedback highlighted in reviews (e.g., staff unprofessionalism or unreliable Wi-Fi) through targeted responses or service improvements, thereby enhancing guest satisfaction and loyalty. Additionally, the model can be integrated into an automated monitoring system to filter negative reviews early, enabling timely interventions to mitigate potential reputational damage and improve operational efficiency in real-time hospitality management.

Table 5. Comparison of Baseline Models vs. BiLSTM

Model	Accuracy	Precision	Recall	F1-Score
Naive Bayes	0.8500	0.8800	0.8700	0.8750
SVM	0.8700	0.9000	0.8800	0.8900
BiLSTM	0.9017	0.9361	0.9531	0.9445

Table 5 presents a comparative evaluation of three classification models—Naive Bayes, Support Vector Machine (SVM), and Bidirectional Long Short-Term Memory (BiLSTM)—in terms of their performance on sentiment analysis tasks, as measured by accuracy, precision, recall, and F1-score.

The results clearly indicate that the BiLSTM model outperforms the two baseline models across all evaluation metrics. Specifically, BiLSTM achieves the highest accuracy (90.17%), precision (93.61%), recall (95.31%), and F1-score (94.45%). This suggests that the BiLSTM model has a superior ability to correctly identify both positive and negative

sentiments, while maintaining a strong balance between precision and recall.

Compared to Naive Bayes and SVM, which achieved F1-scores of 87.50% and 89.00% respectively, BiLSTM provides a significant performance improvement. These results highlight the advantages of using deep learning architectures—particularly those capable of modeling sequential dependencies in text data—for complex natural language processing tasks such as sentiment classification.

The implications of these findings suggest that the application of BiLSTM can lead to more accurate and reliable sentiment detection in real-world scenarios, such as customer review analysis, especially in domains where nuanced language and context play a critical role. Additionally, the marked improvement in recall indicates that BiLSTM is particularly effective at reducing false negatives, making it valuable for applications where capturing all relevant sentiment expressions is crucial for downstream decision-making processes.

Conclusion

Implementing a BiLSTM model on 10,681 Traveloka hotel reviews demonstrates its effectiveness for sentiment classification in the tourism sector, achieving 90.17% accuracy and a 94.45% F1-score. This success underscores the critical role of preprocessing, vocabulary building, and data balancing techniques such as SMOTE and class weighting in managing imbalanced datasets. Notably, addressing class imbalance within the localized context of Yogyakarta hotel reviews represents a novel contribution, enhancing the model's applicability to regional tourism data. The high performance metrics directly translate into actionable outcomes for hotel management in Yogyakarta, enabling targeted improvements in customer satisfaction and competitive positioning. Stakeholders are encouraged to integrate this BiLSTM-SMOTE approach into operational systems, such as Customer Relationship Management (CRM) platforms, to monitor feedback in real-time and adapt services accordingly, thereby boosting Yogyakarta's tourism competitiveness as evidenced by the empirical results.

The study highlights unique advantages of the BiLSTM-SMOTE combination over prior methods, particularly in handling skewed sentiment distributions, which is a common challenge in localized datasets. However, challenges specific to the Indonesian language—such as informal slang, regional dialects, and code-switching—require further attention in future work. Future research should prioritize a framework for multilingual analysis, focusing on these linguistic complexities, alongside the exploration of transformer-based models like BERT to improve performance and scalability. This prioritized approach will ensure the model's adaptability to diverse linguistic contexts and its scalability for broader tourism applications.

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