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Hotel Reviews Classification and Review-based Recommendation Model Construction using BERT and RoBERTa

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***Abstract*—Personalization plays a crucial role in significantly enhancing customer satisfaction within the hotel industry. Customers, with their unique preferences, often rely on previous customer reviews when selecting a suitable hotel. Therefore, personalization can simplify this process by providing curated lists of hotel recommendations. Our research analyzed six hotel aspects: Value, Accessibility, Service, Room, Cleanliness, and Sleep Quality. We utilize transformer-based NLP models, namely BERT and RoBERTa, to accomplish the analysis. We propose a review classification method to identify customer preferences for each aspect and create a review-based recommendation system for hotel suggestions. To assess performance, we utilize three randomly selected reviews as inputs for both the classification model and the recommendation system. Our findings demonstrate that BERT outperformed RoBERTa in review classification, achieving an accuracy score of 0.8963 and a macro F1 score of 0.83. On the other hand, when constructing a review-based recommendation, RoBERTa proved superior to BERT, with the highest cosine similarity score of 0.99917. Based on our research, we recommend that the hotel industry consider leveraging NLP models, such as BERT and RoBERTa, to create effective personalization strategies. Our research contributes valuable scientific insights into the application of NLP models for creating personalized experiences within the hotel industry.**

***Keywords*—BERT, RoBERTa, Embeddings, NLP, Recommendation System, Hotel Review**

I. Introduction

The hotel industry increasingly adopts a personalized approach to enhance customer experience and satisfaction, maintaining its competitive edge in a dynamic market. As the competition intensifies, hotels strive to provide distinctive value on a personal level [1]. Personalization becomes essential in the hotel industry for creating a customer-centric approach that enhances overall satisfaction [2]. Comprehensive analysis of diverse customer preferences, including room, service, and more, enables hoteliers to create customized offerings that cater precisely to individual needs and desires. By comprehending customer reviews, hoteliers can better understand customer preferences and refine their offerings to enhance satisfaction levels. In this context, customer reviews are crucial, serving as valuable resources that offer insights into individual experiences, preferences [3], and satisfaction levels. By leveraging the implicit value of customer reviews, hotels can implement personalized strategies and provide aligned hotel recommendations that cater to individual customer preferences. This approach ultimately leads to improved customer satisfaction and experiences during hotel stays.

In terms of gaining a comprehensive understanding of customer preference, customer reviews serve as valuable insight that reflects customer opinions, recommendations, and complaints regarding their experience [4]. By utilizing these insights, hoteliers can develop personalized strategies and offer tailored recommendations based on individual customer preferences. This approach allows hoteliers to provide customized services and acknowledges the interconnections between the hotel industry and various aspects of the hospitality sector, such as restaurants, transportation, and infrastructure [5]. An empirical study suggests that customer reviews significantly impact the decision-making process when selecting a hotel. Potential customers rely on reviews from previous guests to evaluate the suitability of a hotel [6], [7]. Therefore, hoteliers need to leverage customer reviews to shape their offerings to align with the needs and expectations of their target customers.

Machine learning algorithms effectively classify hotel customer reviews, thereby enabling the identification of specific customer preferences. The utilization of natural language processing (NLP) allows for the processing of customer reviews and the extraction of valuable insights from textual data [8]. In 2019, Google introduced Bidirectional Encoder Representation from Transformer (BERT), a highly accurate transformer-based NLP model that revolutionized language processing and is pivotal in various applications [9]. The most common use of BERT is to process customer reviews for sentiment analysis, text classification, and question-answering [10], [11]. In addition to BERT, another transformers-based NLP model is RoBERTa, introduced by Facebook. It is an optimized version of BERT that uses a larger dataset and a more complex pre-training process [12]. RoBERTa utilizes dynamic masking during training, generating unique tokens in each phase and achieving superior performance compared to BERT. The architecture of RoBERTa is more complex due to the model being trained using larger data, which benefits RoBERTa in learning more intricate information. Additionally, BERT and RoBERTa employ distinct tokenization methods to convert words into subwords for model input. BERT uses WordPiece tokenizer, segmenting words by frequency in the corpus. In contrast, RoBERTa uses byte-level BPE, allowing finer subword representation and improved handling of rare and out-of-vocabulary terms [13]. Byte-level BPE usage significantly boosts RoBERTa's performance and rare-word handling, enhancing its textual data processing, especially in customer reviews, surpassing BERT's capabilities.

Machine learning is also a popular approach to building recommendation systems. The collaborative filtering (CF) recommendation system construction can effectively employ

BERT and RoBERTa NLP models [14]. The algorithm gathers customer data to predict customers' interest in products. The underlying of the CF approach is that if person A shares the same interest as person B on a particular issue, A is more likely to share B's interest on a different matter than a randomly selected person. The CF recommendation system analyzes user interactions to identify similarities and patterns. This approach exhibits high accuracy and effectively mitigates the cold start problem for users with limited historical data. CF algorithms address data limitations by assessing user similarity to identify and incorporate other users' preferences. This approach effectively mitigates the disparity between limited data availability and user interactions. As K. Zhao and Lu [15] stated, CF efficiently enhances customer satisfaction by offering specific and relevant recommendations to similar users. Furthermore, user preference-based CF enables users to discover less widely recognized hotels that cater to their individual preferences [16].

Our research aims to analyze customer hotel preferences and create a personalized review-based recommendation using BERT and RoBERTa models. While the hotel industry has not widely adopted these models for understanding customer preferences, our study involves two main steps. Firstly, we employ BERT and RoBERTa to classify customer reviews based on their hotel aspect preferences, including Value, Accessibility, Service, Room, Cleanliness, and Sleep Quality. Secondly, we develop a review-based recommendation system to suggest hotels that align with individual customer preferences. Additionally, we compare the performance of the BERT and RoBERTa NLP models. The outcomes of our research significantly benefit the hotel industry by enhancing customer satisfaction and experience through the implementation of effective personalization strategies.

II. Literature Review

The rapid growth of customer reviews has led to increased adoption of deep learning methods, particularly transformer-based NLP models, for processing textual data in machine learning [17]. These transformer-based models employ deep learning as the underlying architecture, extracting features from sentences and representing them as vectors in the embeddings layer [18]. Previous research has extensively used transformer-based NLP models for various tasks, such as Chinese language segmentation [19], subject classification of articles [20], and sentiment analysis of hotel reviews [21], [22]. BERT and RoBERTa have emerged as state-of-the-art models in numerous NLP areas, including the analysis of text-based data like customer reviews [23]. They have been effectively utilized for determining positive and negative topics in hotel reviews [21], classifying sentiment emotions from hotel reviews [24], and evaluating sentiment toward restaurant aspect categories from customer reviews on social media [22].

BERT and RoBERTa can also classify hotel aspect preferences by fine-tuning a hotel review dataset, encompassing value, accessibility, service, room, cleanliness, and sleep quality [25]. In this context, "value" refers to the benefits customers receive beyond the price paid, including the helpful information on the website [26]. "accessibility" evaluates the hotel's location, ensuring it is easily reachable by any transportation mode and close to various supporting places [27]. The "service" aspect encompasses the quality of staff responsiveness, communication, and additional facilities [28]. The "hotel room" aspect involves assessing comfort, ambiance, decoration, equipment, and supporting technology [29]. Factors related to "cleanliness" encompass the bedroom, bathroom, bed, and quality of housekeeping service [30]. Finally, "sleep quality" considers the hotel environment, location, number of floors, room ambiance, comfortable bedding, and pillows [31].

NLP models such as BERT and RoBERTa enable the construction of a review-based recommendation system using feature selection on the embeddings layer [14]. Previous research has applied BERT to predict ratings and provide hotel recommendations [32]. Another research also utilized BERT embeddings for feature selection in building a neural collaborative filtering (CF) recommendation system for news [33]. The CF recommendation system benefits the personalized offering strategy in the hotel industry. These collaborative filtering (CF) systems leverage customer information to offer tailored suggestions based on individual preferences [34]. By identifying patterns and similarities among users, these CF algorithms can provide personalized hotel recommendations based on past booking history, reviews, and preferences. Furthermore, a recent study demonstrated the successful application of RoBERTa in enhancing product recommendations in E-Commerce [35].

III. Research Methodology

We utilize 'bert-based-uncased,' 'bert-base-cased,' and 'roberta-base' for classifying hotel reviews and constructing a recommendation system through the embeddings layer. We calculate user similarities by using cosine similarity based on their preferences input in the hotel review classification process. For a detailed illustration of the process, refer Fig. 1.

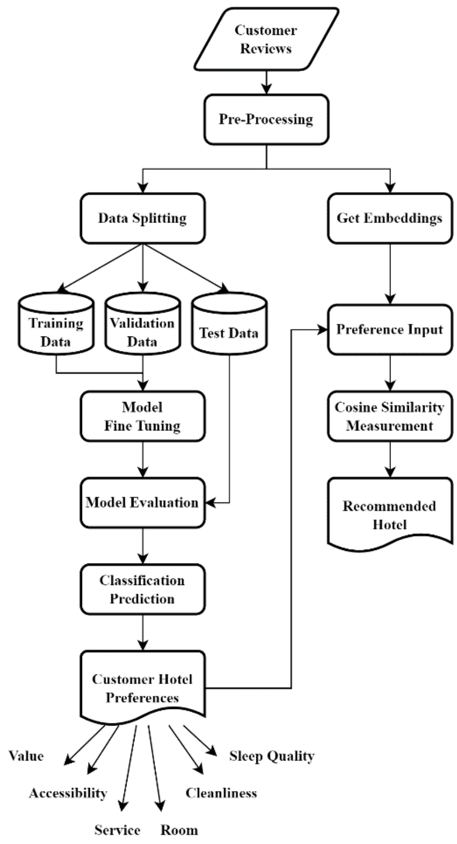

Fig. 1. Research Workflow

A. Data Collection

Data are collected from TripAdvisor, an online hotel booking platform, using Google Chrome Web Scraper Extension. We collected English reviews from international tourists about their stays in Bali hotels, Indonesia. The data consists of English-language reviews from foreign tourists, as the reviewers are primarily from outside Indonesia. The collected data have different characteristics and amounts of data. Table I shows the data summary.

TABLE I. DATA SUMMARY

Data	Description	Total
Location	Hotel location area	16
Hotel	Hotel's name	23
User ID	Reviewer ID	29,343
Review Title	The title of the review	29,343
Review Text	Review of an occupied hotel	29,343
Rating	Rating score from 1 to 5	29,343
Date	The date of the review	29,343

B. Data Labeling

We apply the multilabel technique since the reviews can be classified into multiple categories. There are 5,798 labeled data points with different distributions across six hotel aspects: Value, Accessibility, Service, Room, Cleanliness, and Sleep Quality. Table II shows the difference in each criterion used and the total distribution of labeled data.

TABLE II. LABEL CRITERIA AND DATA DISTRIBUTION

Label	Criteria	Total
Value	The experience exceeds the hotel price	555
Accessibility	Conveniently travel to various places with easy access	2,413
Service	Hotel staff services, including restaurant services	2,677
Room	Features in bedrooms, fittings, spaciousness, and including bathroom	2,691
Cleanliness	The overall cleanliness of the hotel, including the bedrooms	1,702
Sleep Quality	Comfortable bed and get a good sleep	588

C. Data pre-processing

Pre-processing consists of three stages to achieve optimal model performance. First, we eliminate redundant data to enhance data diversity and avoid repetition. The second stage involves removing null data to prevent runtime errors during model training and ensure optimal performance. Third, we perform tokenization using pre-trained BERT and RoBERTa models, which split sentences into individual words. Tokenization automatically removes punctuation marks, eliminating the need for a separate step [36].

D. Fine Tuning BERT and RoBERTa

Fine-tuning involves experimenting with different combinations of batch sizes and learning rates to determine the hyperparameter settings that yield the best model performance. The various hyperparameter are batch sizes of 12 or 16, learning rates of 0.00001, 0.00002, 0.00003, or 0.00005, and 7 epochs. We conduct tests on different hyperparameters to identify the optimal setting of hyperparameters for each pre-trained model: 'bert-base-uncased', 'bert-base-cased', and 'roberta-base'. The data split for training, validation, and testing is 80:10:10 for the three pre-trained models. The data distribution for this research consists of 4,596 training data, 574 validation data, and 574 test data after pre-processing stages. We conduct fine-tuning experiments on the Google Colab Pro platform using Python code version 3.10.

We determine the optimal hyperparameter combination by selecting the training results with the lowest validation loss among the seven epochs. This approach is based on the observation that an increase in validation loss during a specific epoch suggests the presence of overfitting.

The performance evaluation of fine-tuning includes accuracy, precision, recall, and F1 score. Accuracy calculates the percentage of correctly predicted data. Meanwhile, precision and recall measure the model's ability to identify relevant data and make predictions. The F1 score evaluates the overall model's performance. We also selected three TripAdvisor reviews to assess the correctness of our classification model. Table III shows a random selection of reviews from TripAdvisor.

TABLE III. THREE REVIEWS SELECTED

Customer	Reviews Text
A	*suitable for families because the room is big and quite comfortable. I stayed 3 days 2 nights quite satisfied because the room was also clean with complete facilities. the staff is friendly and helpful*
B	*really happy to be able to stay here with my family. the pool is really big really satisfied if you want to swim because there is an elongated layout and there is a jacuzzi too. the rooms are clean and very soundproof the hotel is also in front of a shopping center*
C	*Great staff and great hotel!! I really enjoyed my staff there in February of 2023. I had a great experience, staff was professional and friendly and the hotel had everything I needed. Restaurant, massages, fitness gym and swimming pool!!*

E. Review-based Recommendation System Model

For the review-based recommendation system, we utilize BERT and RoBERTa embeddings layer and employ cosine similarity to calculate the similarity between user preferences. A cosine similarity scores greater than 0.50 indicates a good similarity value. We selected this threshold because cosine similarity relies on the vector angle between the input data and the customer preferences for measuring similarity. A smaller angle corresponds to a better similarity, resulting in a higher score. We rank the hotel suggestion from the highest to the lowest cosine similarity score.

IV. RESULTS

Each pre-trained model achieved a different optimal set of hyperparameters during the fine-tuning process. The lowest validation loss determines the best model of epoch and the optimal set of hyperparameters. Table IV and Table V display the results of hyperparameter combination sets for BERT and RoBERTa, respectively.

TABLE IV. FINE-TUNING RESULT OF BATCH SIZE 12

Pre-Trained Model	Learning Rate	Epoch	Validation Loss
Bert-base-uncased	0.00001	3	0.2634
	0.00002	2	0.2624
	0.00003	2	0.2658
	0.00005	**2**	**0.2566**
Bert-base-cased	0.00001	4	0.2578
	0.00002	2	0.2676

	0.00003	**2**	**0.2556**
	0.00005	2	0.2735
Roberta-base	0.00001	4	0.2717
	0.00002	**2**	**0.2508**
	0.00003	2	0.2627
	0.00005	4	0.2781

TABLE V. FINE-TUNING RESULT OF BATCH SIZE 16

Pre-Trained Model	Learning Rate	Epoch	Validation Loss
Bert-base-uncased	0.00001	4	0.2696
	0.00002	2	0.2571
	0.00003	2	0.2571
	0.00005	**2**	**0.2562**
Bert-base-cased	0.00001	4	0.2686
	0.00002	3	0.2730
	0.00003	**2**	**0.2660**
	0.00005	3	0.2663
Roberta-base	0.00001	3	0.2662
	0.00002	**3**	**0.2586**
	0.00003	3	0.2656
	0.00005	7	0.3443

The results indicate that the combination of hyperparameters influences the performance of the classification model. The 'bert-base-uncased' model achieved the optimal hyperparameters with a validation loss of 0.2562 at epoch 2, using a learning rate of 0.00005 and batch size 16. The ‘bert-base-cased’ pre-trained model attained the optimal hyperparameters setting at epoch 2 with a validation loss of 0.2556, employing a learning rate of 0.00003 and using a batch size of 12. The ‘roberta-base’ model achieved a validation loss of 0.2508 at epoch 2 using a learning rate of 0.00002 and a batch size of 12. The difference in validation loss among the three pre-trained models is insignificant.

We utilized the optimal set of hyperparameters for each pre-trained model to evaluate the model performance. We use the macro F1 score to accurately measure the overall model performance due to the dataset’s imbalance. In our experimental result, the 'bert-base-uncased' model achieved a high accuracy of 0.8963, indicating excellent predictive capabilities. The 'bert-base-uncased' model also achieved the highest precision macro score of 0.83, demonstrating its ability to predict true positive data accurately. Furthermore, the recall macro score of 0.86, achieved by the 'bert-base-cased' pre-trained model, indicates its strong predictive capability for relevant data. The 'bert-base-uncased' and 'bert-base-cased' pre-trained models achieved the highest macro F1 score of 0.83, outperforming the RoBERTa pre-trained model. Table VI presents the details of the model evaluation metrics results.

TABLE VI. MODEL EVALUATION METRICS

Evaluation	Pre-Trained Model		
	bert-base-uncased	***bert-base-cased***	***roberta-base***
Accuracy	**0.8963**	0.8900	0.8905
Precision Macro	**0.83**	0.81	0.81
Recall Macro	0.84	**0.86**	0.84
Macro F1 Score	**0.83**	**0.83**	0.82

The experimental results of the review-based recommendation system show variations in recommendation lists between BERT and RoBERTa. RoBERTa tends to generate higher cosine similarity scores than BERT, while the difference is insignificant. Tables VII to IX display hotel recommendation lists based on customer preferences obtained through classification. The highest cosine similarity score for review A recommendation is 0.99917, achieved by RoBERTa. It demonstrates that RoBERTa has a better suggestion in recommending hotel lists for people with similar preferences to Review A.

TABLE VII. RECOMMENDED HOTEL LISTS OF REVIEW A

Rank	Hotel	Features Recommendation	Similarity Score
Pre-trained model of ‘bert-base-uncased’			
1	The Stones Hotel Legian Bali	Room & Cleanliness	0.99419
2	Atanaya Hotel	Service & Room & Cleanliness	0.99396
3	Mercure Bali Legian	Service & Room	0.99337
Pre-trained model of ‘bert-base-cased’			
1	The Anvaya Beach Resort	Accessibility & Service & Room	0.99759
2	Mercure Bali Legian	Value & Service	0.99755
3	Adiwana Bisma Ubud	Service & Cleanliness	0.99733
Pre-trained model of ‘roberta-base’			
1	Ramayana Candidasa Bali	Service & Cleanliness	**0.99917**
2	Radisson Blu Resort Bali Uluwatu	Accessibility & Room & Cleanliness	0.99910
3	Ulaman Eco Retreat	Service & Cleanliness	0.99909

The ‘roberta-base’ pre-trained model achieves the highest cosine similarity score of 0.99874 for Review B, slightly different from the 'bert-base-cased' pre-trained model's score of 0.99872. It suggests that the ‘roberta-base’ model is better at understanding the meaning of Review B than the 'bert-base-cased' model. Table VIII provides a detailed comparison of cosine similarity between BERT and RoBERTa.

TABLE VIII. RECOMMENDED HOTEL LISTS OF REVIEW B

Rank	Hotel	Features Recommendation	Similarity Score
Pre-trained model of ‘bert-base-uncased’			
1	The Stones Hotel Legian Bali	Accessibility & Room	0.98985
2	Mercure Bali Legian	Service & Room & Cleanliness & Sleep Quality	0.98924
3	Maya Sanur Resort & Spa	Room	0.98783
Pre-trained model of ‘bert-base-cased’			
1	Nusa Dua Beach Hotel & Spa	Accessibility & Room & Cleanliness	0.99872
2	Adiwana Bisma Ubud	Accessibility & Room & Cleanliness	0.99857
3	Ulaman Eco Retreat	Accessibility	0.99833
Pre-trained model of ‘roberta-base’			
1	Mercure Bali Legian	Service	**0.99874**
2	The Stones Hotel Legian Bali	Accessibility & Cleanliness & Sleep Quality	0.99871
3	The Anvaya Beach Resort	Accessibility	0.99864

In addition, the RoBERTa model achieved the highest cosine similarity score of 0.99900 for review C. It is similar to the insignificant difference between the 'roberta-base' and 'bert-base-cased' pre-trained models for review B. More detailed information can be found in Table IX.

TABLE IX. RECOMMENDED HOTEL LISTS OF REVIEW C

Rank	Hotel	Features Recommendation	Similarity Score
Pre-trained model of 'bert-base-uncased'			
1	Mercure Bali Legian	Accessibility & Service & Room	0.99481
2	The Anvaya Beach Resort	Accessibility & Service	0.99471
3	Ramayana Candidasa Bali	Service & Room & Cleanliness & Sleep Quality	0.99442
Pre-trained model of 'bert-base-cased'			
1	Mercure Bali Legian	Value & Service & Room	0.99861
2	Ramayana Candidasa Bali	Accessibility	0.99858
3	The Stones Hotel Legian Bali	Value & Cleanliness	0.99853
Pre-trained model of 'roberta-base'			
1	Mercure Bali Legian	Service	**0.99900**
2	Atanaya Hotel	Accessibility	0.99896
3	Blue Lagon Avia Villas	Service	0.99894

Overall, the experimental results of the review-based recommendation system show that the pre-trained RoBERTa model is superior in providing hotel recommendations based on cosine similarity values. All the pre-trained models can provide recommendations based on customer preferences with insignificant differences in similarity scores. BERT and RoBERTa suggest lists of hotel features effectively.

V. DISCUSSION

The experimental findings demonstrate differences in the classification performance of BERT and RoBERTa. Several factors impact the results. Firstly, the characteristics and complexity of the training dataset significantly influence model performance. Transformer-based models like BERT and RoBERTa are highly dependent on the training data, and BERT's smaller complexity may lead to better performance in processing textual data. Secondly, architectural differences between BERT and RoBERTa affect the efficiency of processing new data. While both models share the same transformer architecture, RoBERTa's pre-training procedure involves a more extensive process. Furthermore, the performance difference in resulting cosine similarity might be attributed to the model's ability to capture contextual meaning. The review-based recommendation system relies heavily on comprehending customer reviews' semantics and context. RoBERTa's advantage in contextual understanding can be attributed to its larger pre-training corpus and more complex architecture than BERT. This result is consistent with the findings of [37], which reported that RoBERTa outperformed BERT in their comparative study.

Based on our findings, the hotel review classification model empowers hoteliers to identify six crucial hotel aspects: Value, Accessibility, Service, Room, Cleanliness, and Sleep Quality. By leveraging the capabilities of BERT and RoBERTa NLP models, this classification system enables hoteliers to create personalized offerings tailored to individual preferences effectively. Personalization is vital for the hotel industry to facilitate marketing management in crafting customized products that align with customer preferences. Furthermore, the implementation of personalization significantly enhances the overall customer experience. The recommendation system offers tailored hotel suggestions based on reviews, saving customers valuable time and fulfilling their specific requirements. By utilizing machine learning insights from customer reviews, this approach facilitates data-driven decisions, optimizes resource allocation, and enhances overall customer satisfaction. The benefits of this personalized recommendation approach extend to hotels, customers, and third-party platforms, fostering customer engagement, loyalty, and efficient hotel searches. Despite the initial investment required for technology implementation, the long-term advantages make it a valuable and rewarding strategy for the hotel industry and online booking platforms.

VI. CONCLUSION

Understanding hotel customer reviews is crucial in examining hotel customer preferences to maintain competitiveness in a dynamic market. Our research analyzes six hotel aspects: Value, Accessibility, Service, Room, Cleanliness, and Sleep Quality using BERT and RoBERTa NLP model. Based on our findings, BERT outperformed RoBERTa in review classification, achieving an accuracy of 0.8963 and a macro F1 score of 0.83. In contrast, RoBERTa surpassed BERT in the review-based recommendation system model, attaining the highest cosine similarity score of 0.99917. Both NLP models effectively predict the hotel aspects and provide suggestions based on customer preferences. It helps hoteliers to create a personalization strategy effectively. Our research also highlights the importance of hoteliers in the digital era leveraging advanced technology to gain a comprehensive understanding of diverse customer preferences. Future research can expand our study by incorporating a larger dataset to develop a review-based recommendation system that includes hotel location and description. It enhances the accuracy of predictions and recommendations. Additionally, exploring another large language model may provide valuable insight into practical areas.

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