iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VI **Month of publication:** June 2026

DOI: https://doi.org/10.22214/ijraset.2026.83732

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

Analyzing Customer Opinions in Tourism Reviews Using Aspect-Based Sentiment Analysis and Machine Learning

Simran Maniyar[1], Dr. Sonali Kulkarni[2], Gaju Chavan[3]
Dr. Babasaheb Ambedkar Marathwada University, Chh. Sambhajinagar

Abstract: ***The high growth rate of online tourism platforms has created a huge amount of reviews by customers which include valuable opinions concerning the tourism services. The reviews are unstructured making it hard to analyze them manually. In this study an aspect-based sentiment analysis (ABSA) system for tourism company reviews is proposed by applying machine learning techniques. The given data was pre-processed by cleaning, tokenization, removing stop words, and feature extraction using TF.IDF values. For sentiment classification, four machine learning classifiers were used: Support Vector Machine (SVM), Random Forest (RF), XGBoost, and Gradient Boosting (GB). The models were tested on the basis of the accuracy, precision, recall, and F1 score. Experimental results revealed that all classifiers had an accuracy rate of more than 97% for excellent performance. The best model was Gradient Boosting with an accuracy of 98.47% among the evaluated models. The proposed framework is able to accurately detect the sentiment of the aspects and can offer valuable insights into the customer's opinion. The results can be used to boost the quality of services offered by the tourism industry, increase customer satisfaction and aid in decision making processes.***

Keywords: Aspect-Based Sentiment Analysis, Tourism Reviews, Machine Learning, XGBoost, Sentiment Analysis, TF-IDF

I. INTRODUCTION

Sentiment Analysis is an important topic in Natural Language Processing (NLP) which deals with recognising and categorising opinions, feelings and attitudes within textual information. It is generally employed to examine customer reviews, social media posts, feedback systems and online comments to see if the expressed sentiment is positive or negative or neutral. In tourism, sentiment analysis can be used to provide insights into customer feedback on various aspects of their travel experience, including their satisfaction with the services they received, the quality of the accommodations, and the friendliness of the staff, among other factors. Organization can assess customer satisfaction, determine service concerns and enhance the overall customer experience by studying customer perspectives.

In most cases, traditional sentiment analysis is done at the document level or sentence level. Document-level sentiment analysis: The overall sentiment polarity of a review or document. Sentence-level sentiment analysis: The sentiment in each sentence of a review or document. These methods can give some indication of what customers think of a company or brand, but they may not give much detail about what they had to say in the review. One tourism review can have several comments on various services. A customer might be pleased with the hotel staff and the experience at the hotel but not with the quality of transport or food. In such cases, the overall sentiment classification may not reflect the customer sentiment towards each service aspect.

To tackle the problem, an advanced sentiment analysis method named Aspect-Based Sentiment Analysis (ABSA) has been proposed as the fine-grained sentiment analysis. In ABSA the aspects or features of the text identified and the sentiment to the aspects are the ones that are focused on, and the sentiment to every aspect is determined separately. Rather than rate the entire review, ABSA identifies key elements like room cleanliness, hotel service, availability of transport facilities, food quality, price, booking process, and staff behaviour and rates each of these elements individually.

Unlike the traditional approaches of sentiment analysis, Aspect-Based Sentiment Analysis offers more detailed and comprehensive insights into customer feedback. It helps tourism companies to pinpoint better and weaker aspects in their offers. For example, it can be seen that the tourism company's accommodation facilities are very satisfactory but the transportation facilities are unsatisfactory. These in-depth analytics enable organizations to make informed decisions, optimize their service delivery, boost customer satisfaction, and fortify their business operations. Accordingly, ABSA is now an important method for the analysis of tourism review data, and for deriving meaningful information from the vast amount of unstructured textual feedback.

©IJRASET: All Rights are Reserved

In the proposed work, the technique of machine learning is implemented for analyzing the customer reviews of the tourism companies such as Support Vector Machine (SVM), Random Forest (RF), XGBoost and Gradient Boosting (GB). The system's aspect-level sentiment classification features provides valuable insights that can be utilized to improve the service quality, increase the satisfaction of the customers, and enable the tourism companies to make better business decisions.

The main contribution of our paper is as follows:

(1) ABSA models were developed for the tourism company review

(2) The ABSA dataset was built by collecting 4500 tourism company review form Maharashtra.

(3) ABSA dataset's labelling guideline was prepared for tourism company review

(4) The paper can be used as a baseline for aspect-based sentiment mining-related research works for tourism company review

II. LITERATURE REVIEW

Pang and Lee published one of the earliest and most influential papers in sentiment analysis and opinion mining. They conducted research on extracting subjective information from text and categorizing opinions as positive and negative. Various machine learning approaches for sentiment classification were discussed and a detailed insight into the techniques of sentiment analysis was provided. Their work laid the groundwork for the research of opinion mining and sentiment analysis [1].

Liu presented a new framework for sentiment analysis and opinion mining, which focused on opinion mining and identification of sentiment orientations and aspect terms from customer reviews. The study emphasized the need for feature based sentiment analysis, which associates sentiments with specific features instead of documents. This way, it gave a more detailed picture of the opinions of customers and served as a primary benchmark in the field of Aspect-Based Sentiment Analysis (ABSA) studies [2].

To mine and summarize customer reviews that describe product features and the sentiments towards them, Hu and Liu suggested a method. They took a method of association rule mining to find frequently occurring features from the review texts, then matched them up with opinion words to decide the polarity of sentiment. This work is considered as one of the early works on aspect-level sentiment analysis [3].

Pontiki et al. hosted SemEval-2014 Task 4: Aspect-Based Sentiment Analysis to make benchmark datasets and evaluation frameworks available for aspect extraction and sentiment classification. Their efforts were a huge leap forward for ABSA research because researchers could analyze various methods using the same standard data sets. The tasks from the SemEval continue to be popular benchmarks in SENTIMENT ANALYSIS research [4].

Breiman introduced the Random Forest algorithm, a multiple decision trees ensemble learning method. It combines multiple trees' predictions and mitigates overfitting to enhance the model's ability to classify. Random Forest has been found to be a very robust supervised learning technique and is used to perform very well in text classification and sentiment analysis applications [5] with complex datasets. In this work, Chen and Guestrin proposed XGBoost, an optimized framework of gradient boosting for boosting prediction accuracy and computational efficiency. The model is regularized and has the mechanisms of sequential learning to enhance the performance. The experimental results indicated the ability of XGBoost to be outperforming many of the traditional machine learning algorithms in the field of sentiment classification, which makes it highly suitable for the sentiment classification tasks [6]. Friedman introduced the Gradient Boosting Machine (GBM), one of the ensemble learning methods that adds weak learners in an iterative manner to create a more powerful predictive model. The algorithm is trained by optimizing a loss function to minimize the number of classification errors. Gradient Boosting is one of the most successful techniques for sentiment analysis and text classification problems [7].

Xiang et al. studied guest experiences at the hotel using online review mining and text analytics. Their research found that they provide useful information about service quality and customer satisfaction from reviews created by customers. The results revealed that sentiment analysis is a critical component in the tourism and hospitality domain and demonstrated its application in online reviews to aid in tourism service improvement strategies [8].

Park et al. utilized machine learning approach to implement A B S A in tourism reviews. The research was aimed on the extraction of tourism related aspects (accommodation, transportation, food services). The experimental results showed that aspect-level sentiment mining algorithms can successfully capture and learn aspect-level sentiments, and give insightful information on customer experiences in tourism [9]

Transformers are introduced by Devlin et al. in the paper BERT: A transformer-based language representation model to capture semantic relationships in text by using bidirectional contextual learning. On a variety of natural language processing tasks such as sentiment classification and aspect extraction, BERT had state-of-the-art performance. The model has greatly inspired the research of sentiment analysis and deep learning based ABSA systems in recent years [10].

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

III. METHODOLOGY

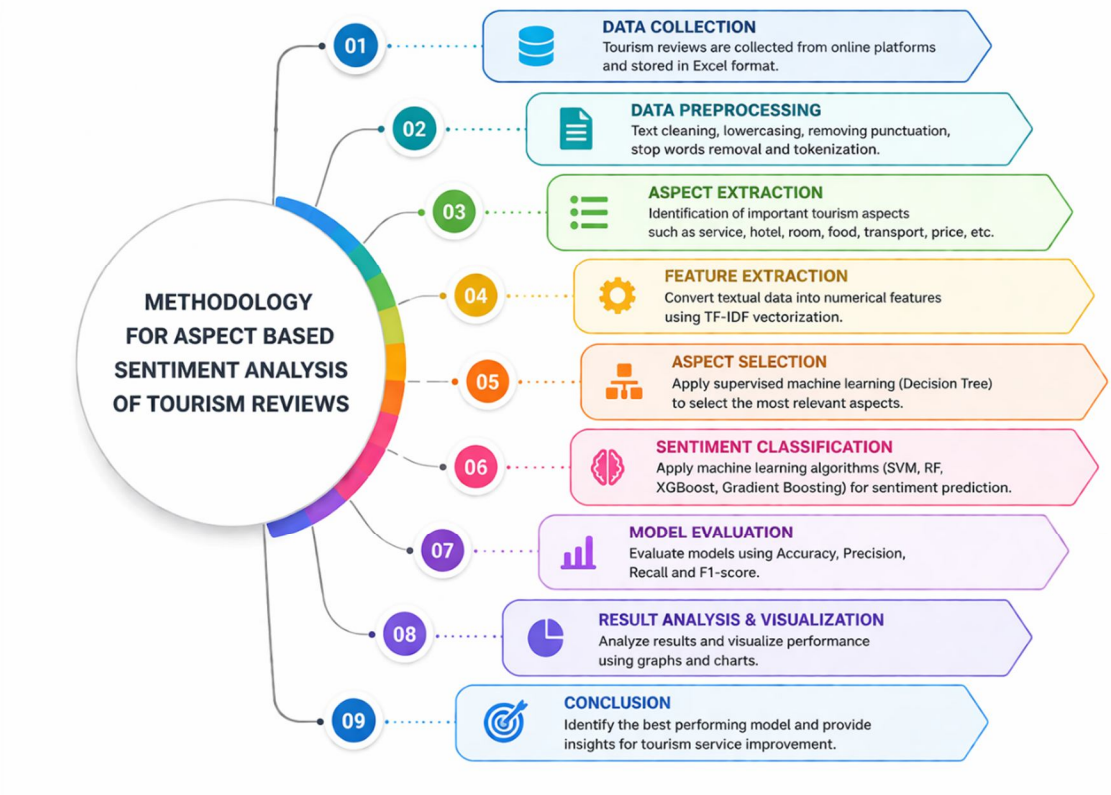


Figure 1: Methodology of ABSA of Tourism review

A. Dataset Description

The tourism review dataset used in this study contains customer feedback collected from online tourism platforms. After aspect extraction, the dataset was transformed into aspect-level sentiment instances to facilitate detailed sentiment analysis. Table 1 presents the overall statistics and sentiment distribution of the dataset used for experimentation.

Table 1: Dataset Summary

Parameter	Count
Total Reviews	4,043
Total Extracted Aspect Instances	4,587
Positive Sentiments	3,259
Negative Sentiments	1,025
Neutral Sentiments	303

This data comes from 4,043 reviews from the tourism companies collected from the internet. A total of 4,587 aspect-level sentiment instances were found after aspect extraction. As seen in the sentiment distribution, the majority of the reviews are positive, followed by negative sentiments and neutral sentiments. The distribution indicates that the majority of the customers had positive feedback for the tourism services and fewer had negative feedback or neutral experiences. The aspect level sentiment annotations were then used for training and evaluation of the machine learning classification models.

B. Data Pre-processing

Raw textual reviews gathered from online platforms are typically unstructured, noisy and inconsistent, and hence, data pre-processing is a crucial step in sentiment analysis and Aspect-Based Sentiment Analysis (ABSA). Customer reviews may include a variety of special characters, punctuation marks, spelling variations, non-relevant words, and other symbols that can impact machine learning models. Hence, the importance of applying pre-processing techniques to pre-process the raw review data to be cleaned and structured for analysis and classification. Before the feature extraction and sentiment classification, several pre-processing stages have been carried out for the tourism reviews dataset in the proposed work. The following are the stages in the pre-processing pipeline:

1) Lowercase Conversion: The words in all review texts were converted to lower case to eliminate the possibility of duplicate words in the text due to case sensitivity. In the example, the terms “Hotel” and “hotel” are considered as the same term after conversion.

2) Remove any punctuation or special characters from the text. Erase punctuation and special characters. In most instances, punctuation, symbols, numbers, URLs and special characters have little to no impact on sentiment analysis. Elements in the review text that are not desired were stripped out to minimize noise and enhance the quality of the text.

3) Tokenization: Tokenization involves breaking down the textual data into smaller entities, typically words or phrases, known as tokens. This step is useful for analyzing words and preparing the text for subsequent steps.

4) Example: Excellent service in the hotel” → [“the”, “hotel”, “service”, “was”, “excellent”] 4. Stop-word Removal: In sentiment analysis, stop-words are words that are very common in the English language, like 'is', 'the', 'was', 'and' and 'of', which have little meaning for the analysis. It is because these words have been removed to make it easier to calculate and compact it.

5) Text Cleaning: More cleaning was done to eliminate unnecessary text patterns, redundant characters, and spaces in the reviews. This will benefit the quality of the data set.

6) We will use TFIDF to extract features from the data. We will use TFIDF for feature extraction. Textual data was pre-processed, and then the features were extracted using the Term Frequency–Inverse Document Frequency (TF-IDF) technique to transform the retrieved data into numerical feature vectors. TF-IDF is used to determine weights for words to highlight the most meaningful ones related to customer sentiment and tourism features, aiding machine learning systems in uncovering important terms. The pre-processing step is one of the key factors that can significantly enhance the performance and precision of machine learning algorithms like Support Vector Machine (SVM), Random Forest (RF), XGBoost, and Gradient Boosting (GB). Pre-processing of text-based reviews transforms unstructured and less meaningful data into structured and meaningfully structured information, thus improving the performance of aspect extraction and sentiment classification tasks.

C. Aspect Categories

The aspect categories are the key attributes, aspects, or services of the tourism experience that tourists often comment on in their reviews in Aspect-Based Sentiment Analysis (ABSA). Knowing these elements can be critical when attempting to pinpoint the tone and opinion of a customer in a review, not just the overall sentiment. The study proposed herein utilises tourism company reviews to identify tourism related aspects that are commonly found. These aspects were chosen because of the type of customer feedback and the services commonly offered by the tourism companies. The sentiments that appear in each review can relate to one or more aspects.

The following are described the major aspect categories considered in this research:

1) Service: This aspect relates to the quality of service offered by the tourism company, responsiveness, assistance and customer support.
Example: “The service provided by the company was excellent.”

2) Staff Behavior: This covers expressions from customers about staff, guides and employees behaviour, professionalism, friendliness and cooperation.
Example: “The staff was very polite and helpful throughout the trip.”

3) Hotel and Accommodation: This aspect is concerned with the hotel facilities, comfort of the rooms, the quality of accommodation, and the overall experience of the stay.
Example: “The hotel rooms were spacious and comfortable.”

4) Food Quality: This category covers perceptions of food, breakfast, restaurant service and food quality during the tour/stay.
Example: The quality of the food was poor and variety was not provided.

5) Transport Services: This aspect includes transport related reviews like vehicle quality, punctuality, comfort and travel arrangements.
Example: Transport service was late and not very comfortable.
6) Pricing: This includes the opinions of customers about the costs of tour packages, their affordability, value for money and extras.
Example: Package price was adequate for the services provided.
7) Booking Experience: These refer to comments on online booking systems, reservations, ticket receipts and payments.
Example: "Easy and fast booking."
8) Destination Experience: This attribute indicates the satisfaction of customers with the tourist attractions, places, sightseeing and travel experience.
Example: The place was beautiful, and they really ought to go there.
9) Cleanliness: It is related to the hygiene and cleanliness of rooms, vehicles, restaurants and tourism facilities.
Example: "The rooms were clean and well-kept.

The aspect categories identified in this study aid in detailed sentiment analysis by linking the opinions of the customers to particular tourism services. This detailed analysis allows tourism businesses to better appreciate customer expectations and go back to the customer with an enhanced service offering through the collection and utilization of customer feedback.

D. Classification Models

Supervised machine learning algorithms were used in the proposed Aspect-Based Sentiment Analysis (ABSA) framework to classify tourism companies into sentiment categories (Positive, Negative, and Neutral sentiment). The textual reviews were then pre-processed and converted to numerical feature vectors using the TFIDF feature extraction technique. These feature vectors were then fed to various classifiers such as Support Vector Machine (SVM), Random Forest (RF), XGBoost (XGB) and Gradient Boosting (GB). By applying more than one type of classifiers, the performance of these classifiers could be compared and the model which is best for classification of sentiment of tourism review could be identified..

1) Support Vector Machine (SVM)

Texts datasets are typically high dimensional and sparse, created by techniques such as TF-IDF vectorization, and are widely used in text classification and sentiment analysis, for which there exists a widely used supervised learning algorithm called Support Vector Machine (SVM) that is applicable. SVM tries to classify sentiment classes with the maximum margin between classes.
In a binary classification problem, the decision surface of SVM can be depicted as:

$$w \cdot x + b = 0$$

Where:

- (w) represents the weight vector
- (x) represents the input feature vector
- (b) represents the bias term

The classification function is:

$$f(x) = \text{sign}(w \cdot x + b)$$

This project used a linear kernel as linear features are used in many sentiment classification tasks and are high dimensional in TF-IDF features. The following parameter was used:

- kernel='linear'

The linear kernel is simple to compute and is used for text data. Because customer reviews tend to have high dimensional patterns of text and be sparse, SVM is appropriate for tourism reviews.

2) Random Forest (RF)

Random Forest is an ensemble learning algorithm which is a combination of different decision trees to create a better prediction. Random subsets of the data and features are used for each individual decision tree and the final prediction is based on majority voting.
The representation of the prediction function of the Random Forest is:

$$\hat{y} = \text{mode}\{T_1(x), T_2(x), \ldots, T_n(x)\}$$

Where:

- (T_1, T_2, ..., T_n) represent individual decision trees
- (\hat{y}) represents the final predicted class

In this project, the following parameter was used:

- n_estimators = 200

This parameter indicates the number of trees in the forest. More trees makes for more stable models and decreases the chance of overfitting. Random Forest was chosen since tourism review data may have various different text patterns and opinions are often noisy, making ensemble tree based learning suitable.

3) XGBoost

The XGBoost (Extreme Gradient Boosting) is an optimized boosting algorithm, where an improvement in weak learners is made sequentially to reduce the error of the prediction. It performs very well on classification problems that are complex in terms of feature relationships. The XGBoost objective function is given by:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Where:

- (l(y_i, \hat{y}_i)) represents the loss function
- (\Omega(f_k)) represents regularization
- (K) represents the number of trees

The following parameters were used in the project:

- n_estimators = 200
- learning_rate = 0.1
- max_depth = 6
- objective = 'multi:softmax'

The learning_rate parameter specifies the amount of contribution to the model of each tree. The max_depth parameter helps to prevent overfitting and makes the tree less complex. The multi:softmax objective function can be used for multi-class sentiment classification. The tourism review dataset is complex due to the non-linear patterns in the text and the sentiment relationships between the reviews, making XGBoost a suitable model to use.Customer reviews are complex in the tourism review dataset as they have complicated sentiment relationships and non-linear textual patterns. This boosting process gradually enhances the classification accuracy by correcting past classification errors.

4) Gradient Boosting (GB)

Gradient Boosting is another ensemble learning technique that builds models sequentially, where each new model attempts to reduce the residual errors generated by previous models.

The Gradient Boosting prediction model is represented as: Another ensemble learning method is Gradient Boosting, which constructs models in sequence, with each new model trying to decrease the errors left by the previous models.

The Gradient Boosting prediction model is given by:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

Where:

(F_m(x)) is the new model

- (h_m(x)) is the weak learner

(\gamma_m) is the learning rate

The following parameters were used:

- n_estimators = 200
- learning_rate = 0.1

The sequential learning mechanism enables Gradient Boosting to make predictions more and more accurate while trying to reduce classification errors. This model proves useful in tourism review sentiment analysis as it considers the complex textual relationships and optimizes the classification performance by iterative optimization.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

The chosen machine learning models are extremely appropriate to the tourism review datasets as they have unstructured textual data, high dimensional TF-IDF features, and mixed sentiment expressions. Random Forest, XGBoost, and Gradient Boosting are good ensemble models for capturing the non-linear relationships between features, and SVM works well for sparse textual representations. Comparative analysis of these models helps to identify the best model as a classifier for Aspect Based Sentiment Analysis of Tourism Company Reviews.

IV. EXPERIMENTAL RESULTS

In order to test the proposed Aspect-Based Sentiment Analysis framework, four machine learning algorithms were implemented and tested: Support Vector Machine (SVM), Random Forest (RF), XGBoost and Gradient Boosting (GB). The dataset was initially pre-processed and then represented as numerical feature vectors using TF-IDF method. The transformed data was then split as 80% training set and 20% testing set. Standard evaluation metrics such as Accuracy, Precision, Recall and F1-scores were used for the assessment of the performance of each model. These metrics offer a complete view of how well the models can classify the tourism reviews into the Positive, Negative and Neutral sentiment classes. All the classifiers are compared and the outcome is shown in Table 2.

Table 2. Performance Comparison of Machine Learning Models for Tourism Review Sentiment Classification

Model	Accuracy (%)	Precision	Recall	F1-Score
SVM	97.49	0.98	0.97	0.97
Random Forest	97.71	0.98	0.98	0.98
XGBoost	97.71	0.98	0.98	0.98
Gradient Boosting	98.47	0.98	0.98	0.98

Four machine learning algorithms (SVM, Random Forest (RF), XGBoost, and Gradient Boosting (GB)) are tested on the tourism review dataset with the metrics of Accuracy, Precision, Recall, and F1-score. The experimental results showed the excellent classification performance of all the models, with accuracy values >97%. Gradient Boosting had the best classification accuracy among the models evaluated at 98.47% followed by SVM (97.49%), Random Forest (97.71%) and XGBoost (97.71%). The model also took an average of 0.98 on Precision, Recall and F1 score for tourism review sentiment classification, showing the effectiveness of the model. The class-wise evaluation of Gradient Boosting showed excellent performance for both Negative and Positive sentiment class with F1 score of 0.99. The relatively small number of neutral reviews in the dataset caused the F1-class to get a slightly lower score of 0.92. However, the model was still very accurate (1.00) for the Neutral class suggesting very accurate predictions for neutral sentiment.

Experimental results indicate that ensemble-based boosting methods are very suitable for tourism reviews sentiment analysis. Gradient Boosting is even better than other methods since it uses an iterative learning approach that reduces classification errors by sequentially creating weak learners. So, a Gradient Boosting was found as the best model in this study for Aspect-Based Sentiment Analysis of Tourism Company Reviews.

V. CONCLUSION

This study aimed to present a framework for sentiment analysis of tourism company reviews in terms of Aspect-Based Sentiment Analysis (ABSA) using machine learning techniques. The review data was pre-processed and made into numerical features with the TF-IDF technique. For sentiment classification, four machine learning models were used: SVM, random forest, XGBoost, and gradient boosting. The results obtained from the experiments demonstrated that the classification accuracy for all the models was high above 97%. Of these, Gradient Boosting gave the best results with an accuracy of 98.47%. The results show the high efficiency of machine learning techniques in detecting customer sentiment from tourism reviews. The proposed framework gives in-depth knowledge about the opinions of customers on various aspects of tourism. The lessons learned may be used to enhance the level of service and satisfaction for tourists. In general, the study showed the significance of aspect level sentiment analysis for tourism review mining and decision making. Transformer and deep learning models could be explored in future to improve classification accuracy.

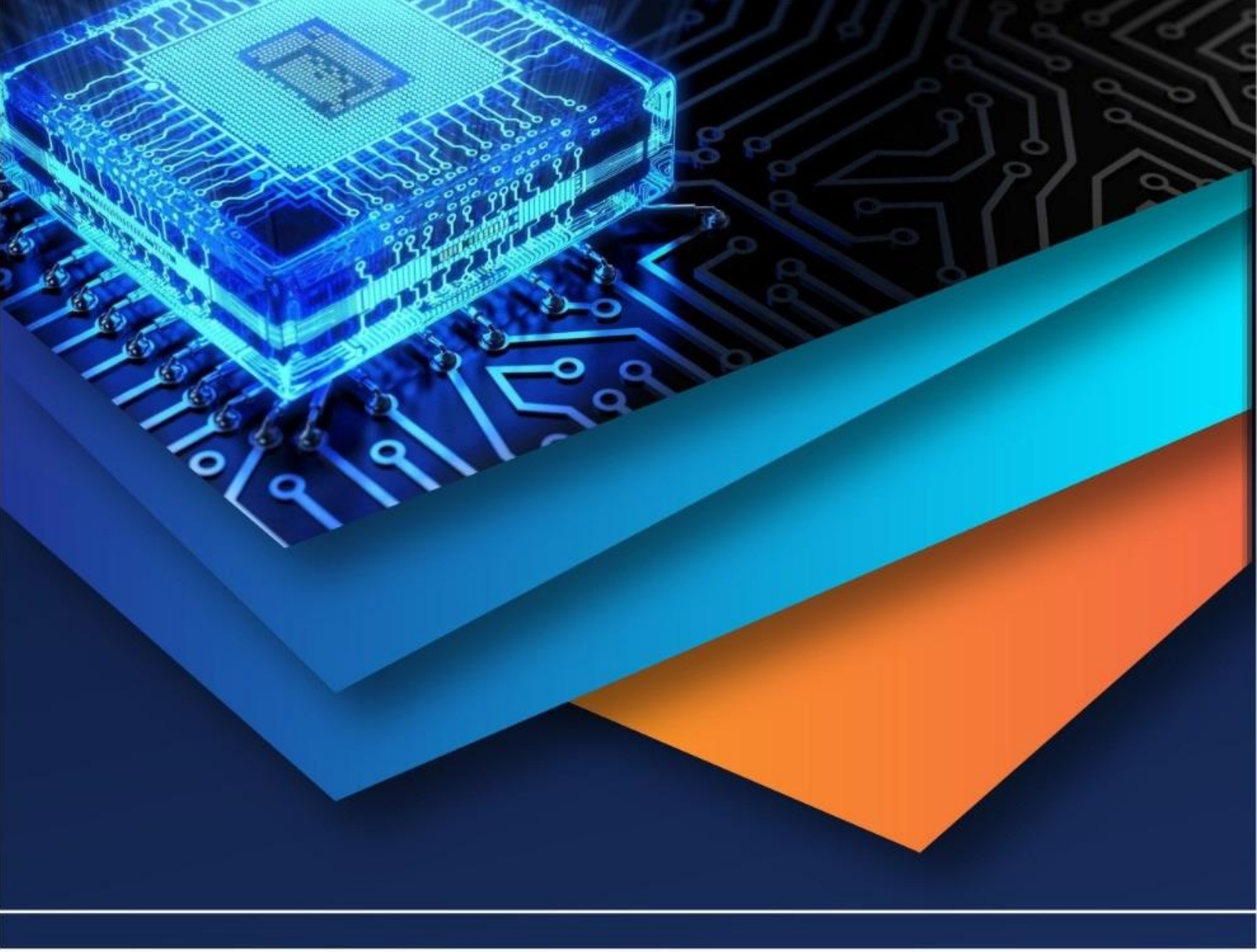
©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

A. Future Work

Future research can explore advanced deep learning and transformer-based models such as LSTM, BERT, and RoBERTa to improve aspect extraction and sentiment classification accuracy. Additionally, multilingual tourism reviews and real-time sentiment monitoring systems can be incorporated to enhance the applicability and scalability of the proposed framework.

REFERENCES

[1] B. Pang and L. Lee, "Opinion Mining and Sentiment Analysis," Foundations and Trends in Information Retrieval, vol. 2, no. 1–2, pp. 1–135, 2008.
[2] B. Liu, Sentiment Analysis and Opinion Mining. San Rafael, CA, USA: Morgan & Claypool Publishers, 2012.
[3] M. Hu and B. Liu, "Mining and Summarizing Customer Reviews," in Proc. 10th ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, Seattle, WA, USA, 2004, pp. 168–177.
[4] M. Pontiki et al., "SemEval-2014 Task 4: Aspect Based Sentiment Analysis," in Proc. 8th Int. Workshop Semantic Evaluation (SemEval), Dublin, Ireland, 2014, pp. 27–35.
[5] M. Pontiki et al., "SemEval-2015 Task 12: Aspect Based Sentiment Analysis," in Proc. 9th Int. Workshop Semantic Evaluation (SemEval), Denver, CO, USA, 2015, pp. 486–495.
[6] M. Pontiki et al., "SemEval-2016 Task 5: Aspect Based Sentiment Analysis," in Proc. 10th Int. Workshop Semantic Evaluation (SemEval), San Diego, CA, USA, 2016, pp. 19–30.
[7] L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
[8] J. H. Friedman, "Greedy Function Approximation: A Gradient Boosting Machine," Annals of Statistics, vol. 29, no. 5, pp. 1189–1232, 2001.
[9] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, San Francisco, CA, USA, 2016, pp. 785–794.
[10] T. Joachims, "Text Categorization with Support Vector Machines: Learning with Many Relevant Features," in Proc. European Conf. Machine Learning, Chemnitz, Germany, 1998, pp. 137–142.
[11] E. Cambria and B. White, "Jumping NLP Curves: A Review of Natural Language Processing Research," IEEE Computational Intelligence Magazine, vol. 9, no. 2, pp. 48–57, 2014.
[12] R. Feldman, "Techniques and Applications for Sentiment Analysis," Communications of the ACM, vol. 56, no. 4, pp. 82–89, 2013.
[13] S. Kiritchenko, X. Zhu, and S. M. Mohammad, "Sentiment Analysis of Short Informal Texts," Journal of Artificial Intelligence Research, vol. 50, pp. 723–762, 2014.
[14] Z. Xiang, Z. Schwartz, J. H. Gerdes, and M. Uysal, "What Can Big Data and Text Analytics Tell Us About Hotel Guest Experience and Satisfaction?" International Journal of Hospitality Management, vol. 44, pp. 120–130, 2015.
[15] J. K. Ayeh, N. Au, and R. Law, "Do We Believe in TripAdvisor? Examining Credibility Perceptions and Online Travelers' Attitude Toward Using User-Generated Content," Journal of Travel Research, vol. 52, no. 4, pp. 437–452, 2013.
[16] S. Park, N. Lee, and J. Han, "Aspect-Level Sentiment Analysis in Tourism Reviews Using Machine Learning Techniques," Expert Systems with Applications, vol. 120, pp. 312–324, 2019.
[17] S. Ruder, P. Ghaffari, and J. G. Breslin, "A Hierarchical Model of Reviews for Aspect-Based Sentiment Analysis," in Proc. EMNLP, Austin, TX, USA, 2016, pp. 999–1005.
[18] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.
[19] X. Zhang, J. Zhao, and Y. LeCun, "Character-Level Convolutional Networks for Text Classification," Advances in Neural Information Processing Systems, vol. 28, pp. 649–657, 2015.
[20] A. Vaswani et al., "Attention Is All You Need," in Advances in Neural Information Processing Systems, vol. 30, Long Beach, CA, USA, 2017, pp. 5998–6008.
[21] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in Proc. NAACL-HLT, Minneapolis, MN, USA, 2019, pp. 4171–4186.
[22] Y. Liu et al., "RoBERTa: A Robustly Optimized BERT Pretraining Approach," arXiv preprint arXiv:1907.11692, 2019.
[23] J. Brownlee, Machine Learning Mastery with Python. Melbourne, Australia: Machine Learning Mastery, 2020.
[24] K. Ravi and V. Ravi, "A Survey on Opinion Mining and Sentiment Analysis: Tasks, Approaches and Applications," Knowledge-Based Systems, vol. 89, pp. 14–46, 2015.
[25] E. Cambria, D. Das, S. Bandyopadhyay, and A. Feraco, A Practical Guide to Sentiment Analysis. Cham, Switzerland: Springer, 2017.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)