IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A Comparative Study of Voting and Stacking Ensemble Models for Sentiment Analysis on Hotel Reviews

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Abstract : Online hotel reviews provide valuable insights into customer experiences; however, such reviews are often short and informal, making automated sentiment analysis challenging. Single classification models frequently struggle to capture sentiment accurately due to limited contextual information and lexical variability. To address this issue, this paper presents a comparative study of voting-based and stacking-based ensemble learning methods for sentiment analysis of hotel reviews. Reviews are preprocessed and decomposed into bigram phrases to analyze the sentimentsin hotel reviews. Multiple feature representations including TF-IDF, Word2Vec, and BERT embeddings are employed to capture lexical, semantic, and contextual information. In the voting ensemble, independent classifiers aggregate predictions using soft voting, while the stacking ensemble integrates base learner outputs through a meta-classifier. Experimental results demonstrate that stacking ensembles achieve more consistent performance on ambiguous hotel review phrases, whereas voting ensembles provide a computationally efficient and reliable baseline. The findings highlight the effectiveness of ensemble strategies for short-text sentiment analysis in hospitality review systems.

Keywords: Sentiment Analysis, Hotel Reviews, Ensemble Learning, Voting Ensemble, Stacking Ensemble ,Short Text Classification, Bigrams, Deep Language Models

1. Introduction

Hotel reviews are becoming an essential tool for both travellers and hotel managers looking to enhance service quality due to the explosive expansion of internet travel platforms. These reviews usually include short remarks or words like "location close to metro," "staff not helpful," or "room very clean." Despite being brief, this type of input has a lot of sentiment, which makes it difficult for conventional sentiment analysis methods that depend on lengthier contextual signals.

The short and fragmented nature of hotel reviews frequently results in sparse representations and unclear sentiment expressions when attempting to discern sentiment polarity, which lowers the efficacy of single-model classifiers. When applied to restricted textual input, deep contextual models may experience overfitting, whereas models based only on lexical features may ignore semantic links.

By integrating several classifiers that have been trained on various feature representations, ensemble learning offers a practical solution. While stacking-based ensembles provide

a meta-learning layer that can learn the best combinations of underlying models, voting-based ensembles provide simplicity and robustness by combining independent predictions. A direct comparison of voting and stacking ensembles for brief, targeted hotel review phrases is still lacking, despite their demonstrated efficacy in general sentiment analysis.

This study compares voting-based and stacking-based ensemble approaches for sentiment analysis of hotel reviews. The work attempts to determine the best ensemble technique for reliable and accurate sentiment classification in hotel review analytics by combining TF–IDF, Word2Vec, and BERT representations and concentrating on bigram-level phrases.

2. Literature Review

Due to the extensive usage of online travel sites like Trip Advisor, Booking.com, and Yelp, sentiment analysis of hotel reviews has drawn increasing attention. Customers' decisions are influenced by the vast amounts of user-generated content seen on these platforms. Automated sentiment classification faces difficulties because hotel reviews are usually brief, informal, and subjective. Previous research shows that sentiment analysis at the sentence and phrase levels is superior than document-level methods for precisely identifying polarity in succinct hotel reviews [1,2].

N-gram-based text representations have been extensively investigated as a solution to the sparsity and heterogeneity of brief hotel evaluations. In particular, bigram representations have demonstrated efficacy in capturing sentiment-bearing statements that unigram-based models frequently overlook, such as "room clean" and "staff rude" [3, 4]. Bigrams reduce noise in short-text classification tasks and enhance sentiment signal clarity by maintaining local word order.

Transformer-based models for sentiment analysis are now widely used due to recent developments in deep learning. By identifying contextual relationships in brief review texts, models like BERT have proven to perform well [5,6]. However, when applied separately to brief and unclear hotel reviews, transformer-based models are computationally demanding and may show erratic predictions, which encourages the investigation of additional modeling techniques.

By mixing predictions from several models, ensemble learning has become a successful method for enhancing sentiment categorization performance. In comparison to single-model techniques, voting-based ensembles have been demonstrated to increase robustness and decrease variance by aggregating outputs from heterogeneous classifiers [7,8]. For noisy user-generated content, soft voting techniques that average predicted class probabilities work very well.

A meta-learning layer that learns the best combinations of basic learner predictions is introduced via more sophisticated ensemble procedures like stacking. In hotel review sentiment categorisation, recent research shows that stacking ensembles incorporating lexical, semantic, and contextual representations perform better than voting ensembles and independent deep learning models [9,10]. Despite these developments, only a small amount of research has used phrase-level representations to systematically compare voting and stacking ensembles within a single experimental paradigm.

Motivated by this gap, the current work uses bigram-level representations and heterogeneous feature views to compare voting-based and stacking-based ensemble models for sentiment classification of hotel reviews.

3. Methodology

This section presents the proposed ensemble-based framework for sentiment analysis of hotel reviews. The technology combines heterogeneous feature extraction and ensemble learning techniques with bigram-level representations to efficiently handle review phrases. Data collection, preprocessing, bigram extraction, feature representation, ensemble model building, and evaluation make up the overall framework [11,12].

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3.1 Dataset Description

The hotel reviews gathered from websites like Yelp and TripAdvisor make up the dataset used in this study.

Sentiment polarity labels Positive, Negative, and Neutral are attached to each review, which highlights important hotel features like location, cleanliness, staff conduct, and room quality. As indicated in the Table 1, the assessments are usually brief—between five to thirty words—and frequently contain concise statements. Due to their high lexical diversity and limited context, short-form reviews pose special difficulties, necessitating the use of robust sentiment modelling [13].

Each review is preprocessed and broken down into bigram phrases to capture significant opinion units, like "room clean," "staff rude," or "location convenient," due to the short evaluations' low context and variety. The ensemble models use these bigrams as their main input. By maintaining the natural distribution of sentiment classes and linguistic patterns in hotel reviews, using the original dataset without augmentation guarantees that the models are trained and assessed on real customer feedback [14].

ID	Original Review
R1	The room was very clean and comfortable
R2	Staff were rude at the reception
R3	The hotel location is very convenient
R4	The room was not clean
R5	Service quality was excellent
R6	The price was too expensive
R7	Breakfast options were limited
R8	The staff were helpful and polite
R9	The bathroom was dirty
R10	Overall stay was satisfactory

Table 1 :Sample Reviews

3.2 Text Preprocessing and Bigram Extraction

Each review is preprocessed and broken down into bigram phrases to capture significant opinion units, like "room clean," "staff rude," or "location convenient," due to the short evaluations' low context and variety. The ensemble models use these bigrams as their main input. By maintaining the natural distribution of sentiment classes and linguistic patterns in hotel reviews, using the original dataset without augmentation guarantees that the models are trained and assessed on real customer feedback [14]. Each review is broken down into bigrams after preprocessing, as seen in Table 2. Phrase-level sentiment data, which are frequently

ID	Extracted Bigrams
R1	room clean, clean comfortable
R2	staff rude, rude reception
R3	hotel location, location convenient
R4	room not_clean
R5	service quality, quality excellent
R6	price too, too expensive
R7	breakfast option, option limited
R8	staff helpful, helpful polite
R9	bathroom dirty
R10	overall stay, stay satisfactory

Table.2 .Bigram Extraction

seen in hotel reviews, can be extracted using bigram extraction. This approach reduces irrelevant noise and focuses the classification process on compact and informative linguistic units [16].

3.3 Feature Representation

Three feature representations are used to encode each chosen bigram in order to capture a variety of linguistic characteristics. TF-IDF vectors capture surface-level lexical patterns by quantifying the significance of words in the corpus, highlighting sentiment-bearing phrases like clean, rude, and expensive. By simulating word co-occurrence patterns, Word2Vec embeddings produce dense semantic vectors [17]. This increases generalisation [18] across a variety of expressions by enabling semantically comparable expressions (such as dirty and unclean) to be positioned near together in the vector space.BERT embeddings provide contextualized representations by encoding word meaning based onsurrounding context; even for short bigrams, BERT captures nuanced sentiment information, making it particularly effective for handling ambiguous or mixed

Bigram	TF–IDF (Lexical)	Word2Vec (Semantic)	BERT (Contextual)
room clean	High weight on *clean*	close to *spotless*	positive cleanliness
staff rude	High weight on *rude*	close to *impolite*	strong negative tone
room not_clean	negation-aware	close to *dirty*	explicit negative
quality excellent	high polarity	close to *great*	strong positive

Table.3. Feature Representation using TF-IDF,Word2Vec

sentiment and BERT hotel review phrases [19]. The combination of these three feature representations ensures that the ensemble models have access to complementary lexical, semantic, and contextual information for accurate sentiment classification [20].

3.4 Voting-Based Ensemble Model

In the voting-based ensemble, three independent classifiers are trained in parallel, each operating on a different feature representation of the input text: TF–IDF features are used with a Logistic Regression model, Word2Vec embeddings with a Random Forest, and BERT embeddings with a Support Vector Machine.Lexical importance, semantic similarity, and contextual meaning enhance the information

Review	LR (TF–IDF)	RF (Word2Vec)	SVM (BERT)	Sentiment
R1	P=0.85	P=0.80	P=0.90	Positive
R2	N=0.88	N=0.83	N=0.92	Negative
R4	N=0.75	N=0.78	N=0.85	Negative
R10	Neu=0.55	Neu=0.60	Neu=0.58	Neutral

Table. 4 Voting based Ensemble

that each feature type captures, enabling the ensemble to take advantage of diverse perspectives. Three separate classifiers are trained simultaneously in the voting-based ensemble, each using a distinct feature representation of the input text: Word2Vec embeddings with a Random Forest, TF–IDF features with a Logistic Regression model, and BERT embeddings with a Support Vector enables the ensemble to take use of a variety of viewpoints. For every input word or bigram, each base learner generates a probability distribution over the sentiment classes (Neutral, Negative, and Positive) [20].

3.5 Stacking-Based Ensemble Model

In the stacking-based ensemble,three base learners Logistic Regression with TF–IDF features, Random Forest with Word2Vec embeddings, and Support Vector Machine with BERT embeddings are first trained independently to generate probability predictions for each sentiment class as shown in Table 5. These outputs are then concatenated to form a meta-feature vector, which serves as input to a Level-2 meta-classifier, such as Logistic Regression or LightGBM [22]. The meta-learner learns to optimally combine the predictions of the base models, assigning adaptive importance to each based on their performance.

Review	LR_ Pos	RF_ Pos	SVM_ Pos	LR_ Neg	RF_ Neg	SVM_ Neg
R1	0.85	0.80	0.90	0.05	0.10	0.05
R4	0.10	0.12	0.08	0.75	0.78	0.85

Table 5. Level-1 Predictions (Meta-Features)

By leveraging both the diversity of base learners and the learning capability of the meta-classifier, the stacking ensemble produces more accurate and robust sentiment Predictions for hotel review bigrams,

Review	Final Sentiment (Stacking)
R1	Positive
R2	Negative
R4	Negative
R10	Neutral

Table 6: Level-2 Meta-Classifier Output

particularly in cases where individual models provide conflicting or ambiguous outputs. This two-level approach [23] allows the system to capture complementary lexical, semantic, and contextual information while improving generalization on short phrases.

3.6 Model Training and Evaluation

The configuration of the base learners used in the proposed ensemble frameworks, along with their corresponding feature representations and key hyper parameters is summarized in Table 7. Each classifier is deliberately paired with a feature type that best suits its learning characteristics. Logistic Regression is employed with TF–IDF features due to its effectiveness in modeling high-dimensional sparse lexical representations. Random Forest is combined with Word2Vec embeddings to capture nonlinear semantic relationships through ensemble decision trees. Support Vector Machine is applied to BERT embeddings to leverage contextual representations while maintaining strong margin-based classification [24]. To ensure a fair comparison, these base learner configurations are applied uniformly to both voting and stacking ensembles. These basic models' probability outputs are sent into the meta-classifier in the stacking architecture, allowing for the adaptive weighting of individual predictions. Table 2 presents a detailed description of the training arrangement used in this

investigation and guarantees reproducibility.

Base Learner	Feature Type	Key Parameters
Logistic Regression	TF–IDF	L2 regularization, C=1.0
Random Forest	Word2Vec	200 trees, max depth=20
SVM	BERT	RBF kernel, C=1.0
Meta-Learner (Stacking)	Probabilities	Logistic Regression

Table 7.Base Learners and Features

To ensure a balanced class representation, stratified k-fold cross-validation is used in the training of both ensemble models. Standard metrics, such as accuracy, precision, recall, and F1-score, are used to assess performance. A comparative analysis is conducted to assess the relative effectiveness of voting and stacking ensembles for sentiment analysis of hotel review bigrams [25].

4. Results and Discussion

A comparison of ensemble-based sentiment classification models and individual classifiers using hotel review bigrams is presented in this section. Accuracy, Precision, Recall, and F1-score are used for assessing model performance, allowing for a comprehensive assessment of effectiveness on short phrases that frequently have limited context and linguistic variation. Table 8 provides a summary of the qualitative results.

The SVM classifier with BERT embeddings performs the best among the individual base learners, with an accuracy of 86.8% and an F1-score of 86.0%. Because BERT can encode contextual sentiment cues even in brief bigram expressions, it outperforms traditional machine learning models in this regard. The Random Forest model with Word2Vec embeddings and the Logistic Regression model with TF–IDF features, on the other hand, perform significantly worse. This suggests that models that rely on a single feature representation are more sensitive to lexical variation and ambiguous phrasing, which are common in hotel reviews. By combining probability outputs from various base learners, the soft voting ensemble enhances classification performance even more. Table 8 illustrates that the voting ensemble outperforms all individual classifiers with an accuracy of 88.4% and an F1-score

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression (TF–IDF)	81.2	80.6	79.8	80.2
Random Forest (Word2Vec)	82.5	81.9	81.1	81.5
SVM (BERT)	86.8	86.2	85.9	86.0
Voting Ensemble (Soft Voting)	88.4	87.9	87.6	87.7
Stacking Ensemble (Meta-Learner)	91.3	90.8	90.6	90.7

Table 8. Performance Comparison of Ensemble Methods on Hotel Review Bigrams

of 87.7%. This gain demonstrates that by balancing complementary lexical, semantic, and contextual inputs, soft voting effectively reduces individual model bias and improves resilience. Voting offers a well-balanced sentiment prediction across classes, as seen by the consistent improvement in precision and recall.

Model	Positive	Negative	Neutral
Voting	89.2	88.5	85.4
Stacking	92.0	91.1	88.7

Table 9. Class-wise F1-Scores

The stacking ensemble delivers the best overall performance, achieving an accuracy of 91.3% and an F1-score of 90.7%. Unlike voting, which assigns equal importance to each base learner, stacking employs a meta-classifier to learn optimal combinations of base model predictions. This adaptive weighting mechanism proves particularly effective for bigram-level sentiment classification, where conflicting signals may arise from different feature views. By learning which models are more reliable under varying linguistic conditions, the stacking ensemble demonstrates superior generalization and stability.

Overall, the results confirm that ensemble learning significantly enhances sentiment classification performance for hotel review bigrams. While the voting ensemble offers a simple and computationally efficient improvement over

individual models, stacking provides the highest predictive accuracy and robustness. These findings validate the effectiveness of ensemble-based frameworks for sentiment analysis of short hospitality-related texts and highlight the advantages of learned aggregation strategies over fixed combination methods.

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