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Research Article

Implicit Aspect Analysis for Sentiment Classification: A Case Study on Hotel Reviews

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ABSTRACT

Aspect-Based Sentiment Analysis (ABSA) plays a vital role in interpreting user opinions in customer reviews by identifying sentiment polarity linked to specific service aspects. However, traditional ABSA methods largely focus on explicit aspect mentions, often neglecting implicit aspects that are contextually implied. This limitation is especially critical in the hospitality domain, where customer reviews frequently include indirect references to hotel features. This study proposes an implicit aspect analysis framework for sentiment classification using hotel reviews, aiming to improve the detection and interpretation of implicit aspect expressions. A dataset of 2,000 TripAdvisor hotel reviews was collected and manually annotated by linguistic experts for four aspects: staff service, cleanliness, value for money, and location convenience. Each sentence was labeled as either explicitly or implicitly expressing an aspect, with associated sentiment polarity (positive or negative). A two-stage framework was developed: the first stage employed Word2Vec Skip-gram modeling and TF-IDF to construct an implicit aspect corpus; the second stage implemented machine learning and deep learning classifiers—including SVM, LR, MNB, RF, CNN, and LSTM—to predict sentiment. The hybrid feature representation combining TF-IDF and Word2Vec significantly enhanced the model's ability to detect implicit sentiments. Deep learning models, particularly LSTM and CNN, outperformed traditional classifiers in both sentiment polarity classification and implicit aspect association. Clustering results confirmed strong alignment with expert-labeled data, validating the framework's effectiveness. The proposed framework demonstrates substantial improvements in classifying implicit aspects, offering valuable insights for service quality evaluation in hospitality and other domains relying on user-generated content.

Keywords: Implicit aspect analysis, sentiment classification, Word2Vec, hotel reviews, deep learning models

INTRODUCTION

Aspect-based sentiment analysis (ABSA) has become a crucial method in natural language processing for understanding opinions expressed about specific features of products or services. It extends traditional sentiment analysis by not only determining whether a sentiment is positive or negative, but also identifying the particular aspect being evaluated [1], [2], [3], [4], [5]. This capability is especially valuable in industries like hospitality, where customer feedback spans a variety of service elements such as cleanliness, service quality, pricing, and location. While most research in ABSA has focused on explicitly stated aspects—where words like "staff" or "location" are clearly mentioned—many real-world reviews often communicate sentiments indirectly [6], [7], [8].

The challenge lies in identifying and interpreting implicit aspects, which are not directly referenced in the text. In hotel reviews, for instance, a sentence like "Everything sparkled" implies a positive opinion about cleanliness, even though the term "cleanliness" does not appear [9], [10]. Existing models based primarily on keyword extraction or frequency-based features often fail to detect these implicit sentiments, resulting in incomplete or inaccurate sentiment analysis. This limitation prevents businesses from fully capturing customer perspectives, which are often embedded in nuanced or context-dependent language [11], [12], [13], [14].

To address this problem, this study proposes an implicit aspect analysis approach for sentiment classification, using hotel reviews as a case study. The research introduces a two-stage framework: the first stage involves constructing an implicit aspect corpus using Word2Vec Skip-gram modeling, while the second stage develops a sentiment classifier that associates sentiments with implicit aspects through deep learning methods such as LSTM and CNN [15], [16], [17], [18], [19], [20]. This approach integrates both statistical and semantic representations, combining TF-IDF and word embeddings to enhance the model's ability to capture contextual sentiment expressions [21], [22], [23]. The central research question driving this work is: How can an implicit aspect analysis approach be effectively applied to classify sentiment in hotel reviews?

The significance of this research lies in its ability to bridge a critical gap in sentiment analysis by targeting the identification of implicit aspects. By improving the detection of subtle, context-driven sentiments, the proposed method offers businesses a more accurate and comprehensive understanding of customer feedback. Moreover, this framework enhances the adaptability of sentiment analysis systems across domains that rely on subjective reviews [24], [25], [26]. As digital platforms continue to expand the volume of unstructured feedback, tools capable of identifying hidden sentiments will become increasingly vital for service quality assessment, strategic planning, and customer relationship management.

OBJECTIVES

To propose an implicit aspect analysis framework for sentiment classification using hotel reviews, aiming to improve the detection and interpretation of implicit aspect expressions.

METHODS

This study employs a dataset composed of 2,000 hotel reviews collected from TripAdvisor over the past three years. Each review is written in English and reflects a variety of customer experiences related to hotel services. To ensure quality and consistency, three linguistic experts manually annotated the reviews. Each sentence was labeled for sentiment polarity (positive or negative), associated with one of four hotel aspects—staff service, cleanliness, value for money, or location convenience—and further categorized as either explicit (where the aspect is mentioned directly) or implicit (where the aspect is inferred from context). Reviews with neutral sentiment (3-star ratings) were excluded to maintain a binary classification structure. Table 1 summarizes the distribution of aspect-specific sentences across the dataset.

Table 1: Summarization of the Dataset

Hotel Aspects	Explicit	Implicit	Positive	Negative
Staff Service	397	153	380	170
Cleanliness	385	165	290	260
Value Price	300	150	215	235
Location Convenience	333	117	341	109

1. Framework Overview

The overall framework developed in this research. It consists of two major stages. The first stage involves building an implicit aspect corpus using the Skip-gram model from Word2Vec to identify semantically related words based on expert-defined aspect keywords. This corpus enhances the detection of implicit aspect expressions in the dataset. The second stage develops a binary aspect-based sentiment classifier that identifies sentiment polarity and associates it with the relevant aspect in each sentence [15], [16], [17], [18], [19], [20].

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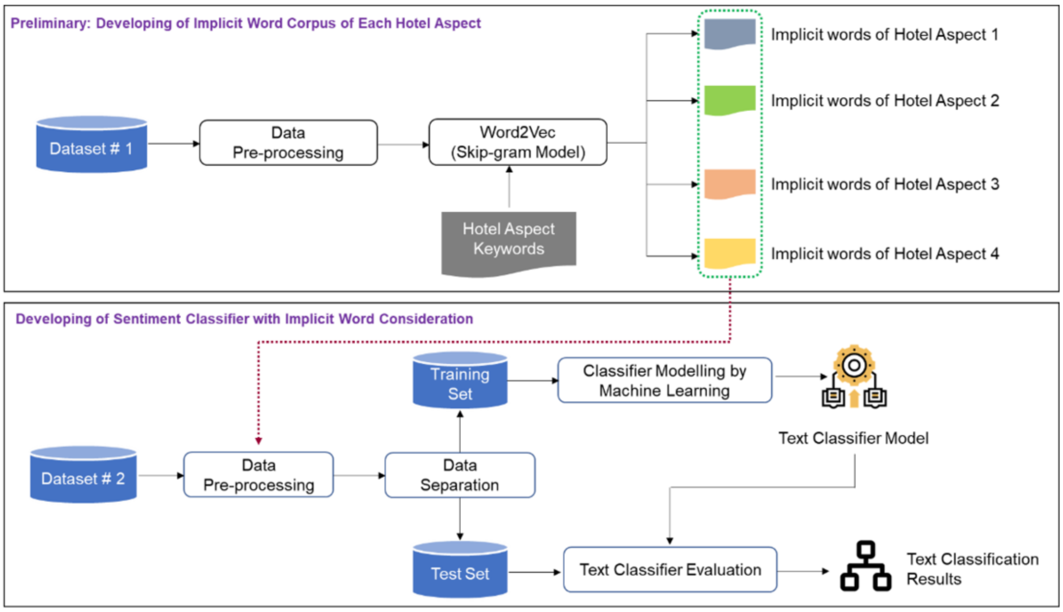

Figure 1: The overall framework developed in this research

2. Text Preprocessing

A comprehensive preprocessing pipeline was implemented to standardize and refine the review data before feature extraction. As shown in Figure 2, the preprocessing steps include converting text to lowercase, removing punctuation, tokenizing sentences using NLTK's tokenizer, eliminating stopwords, and applying lemmatization to reduce words to their base forms. This process ensures that the text input is consistent, reduces noise, and preserves semantic meaning—particularly critical for implicit aspect detection.

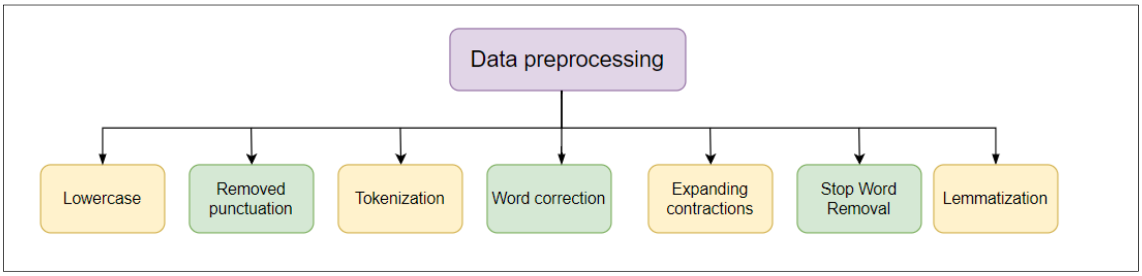

Figure 2: The preprocessing steps include converting text to lowercase

3. Feature Representation

To capture both statistical and semantic information from the text, a hybrid feature representation approach was employed. This method integrates Term Frequency-Inverse Document Frequency (TF-IDF) with Word2Vec embeddings. Each word's Word2Vec embedding is weighted by its corresponding TF-IDF value to emphasize domain-relevant terms while preserving semantic relationships. Figure 3 illustrates this multi-layered process, which enables the model to interpret both surface-level term frequency and deeper contextual associations crucial for identifying implicit aspects.

4. Classifier Modeling

The study evaluates six classification models for sentiment analysis. These include four traditional machine learning algorithms—Support Vector Machine (SVM), Logistic Regression (LR), Multinomial Naïve Bayes (MNB), and Random Forest (RF)—as well as two deep learning models: Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM). Each model was trained and validated using stratified sampling to maintain class balance. The structural architecture and relationships between these models are outlined in Figure 4.

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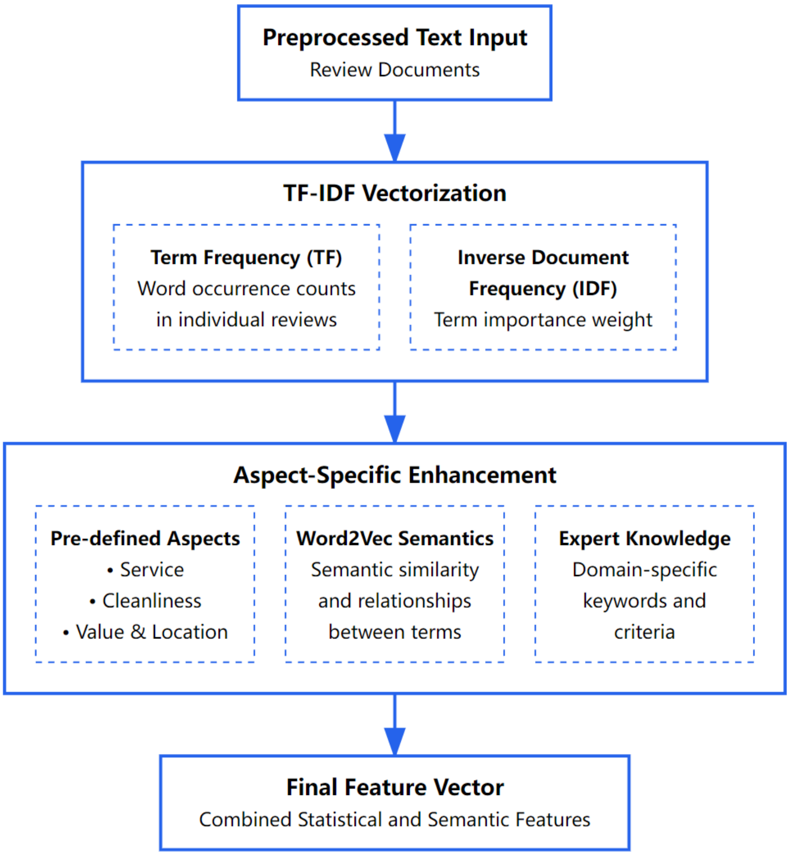

Figure 3: The multi-layered process

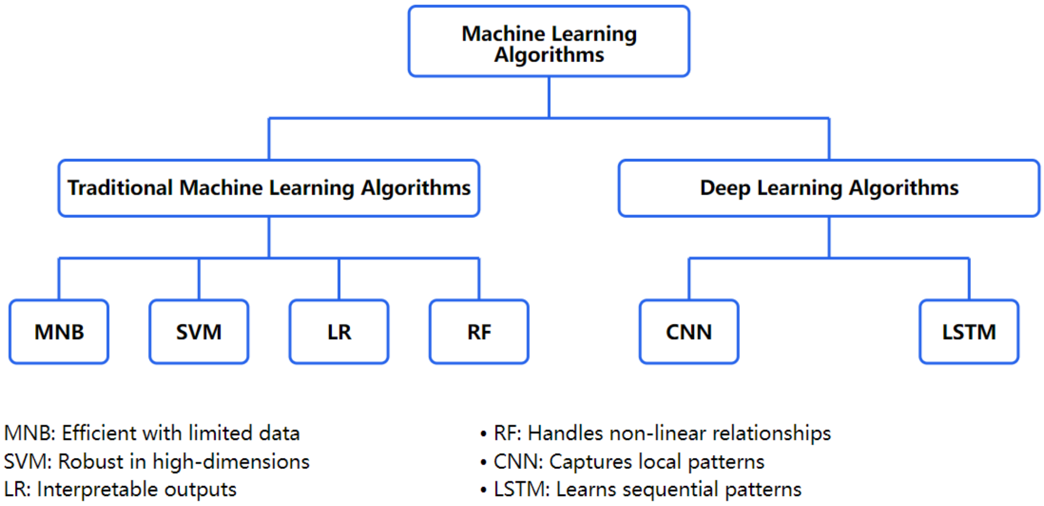

Figure 4: The structural architecture and relationships between these models

5. Evaluation Metrics

To assess the performance of each model, a comprehensive evaluation framework was applied. The evaluation considered six key metrics: Accuracy (the proportion of correctly classified instances), Precision (correct positive predictions over total positive predictions), Recall (correct positive predictions over actual positives), F1-score (the

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harmonic mean of Precision and Recall), AUC (Area Under the ROC Curve), and Aspect Prediction Accuracy (the model's ability to correctly identify the relevant aspect in a sentence). Together, these metrics provide a balanced view of both classification reliability and aspect detection capability.

RESULTS

This section presents the experimental outcomes of the proposed implicit aspect analysis framework, including sentence clustering, aspect type distribution, preprocessing outcomes, and performance evaluation of machine learning and deep learning models. The results illustrate the framework's effectiveness in identifying implicit aspects and classifying sentiment polarity from hotel reviews based on the methodologies described in the previous section.

1. Clustering of Aspect Sentences

To initiate the process of aspect-based sentiment classification, one of the essential steps involved identifying and grouping review sentences according to the underlying hotel service aspect they addressed. Given that many customer sentiments in online reviews are often expressed without explicit references to the aspect in question, this task required an approach capable of discerning subtle semantic cues. In this study, we adopted k-means clustering as a technique to automatically group semantically related sentences using sentence-level vector representations derived from both TF-IDF and Word2Vec embeddings.

Each sentence was transformed into a high-dimensional feature vector reflecting both term frequency and semantic context. This dual representation enabled the clustering algorithm to capture not just surface-level word overlaps but also deeper contextual relationships between words. The k-means algorithm was configured to form four distinct clusters, corresponding to the key aspects of hotel service identified by linguistic experts: staff service, cleanliness, value for money, and location convenience.

As illustrated in Figure 5, the clustering output produced well-separated groups of sentences. These clusters were visualized using dimension reduction techniques (e.g., t-SNE or PCA) to confirm the internal coherence and the boundaries between clusters. The graphical representation of the clusters provided an intuitive understanding of how closely related sentences grouped together, even when their surface vocabulary differed significantly. This is particularly important in identifying implicit aspect expressions, where the aspect is implied through context rather than explicitly mentioned.

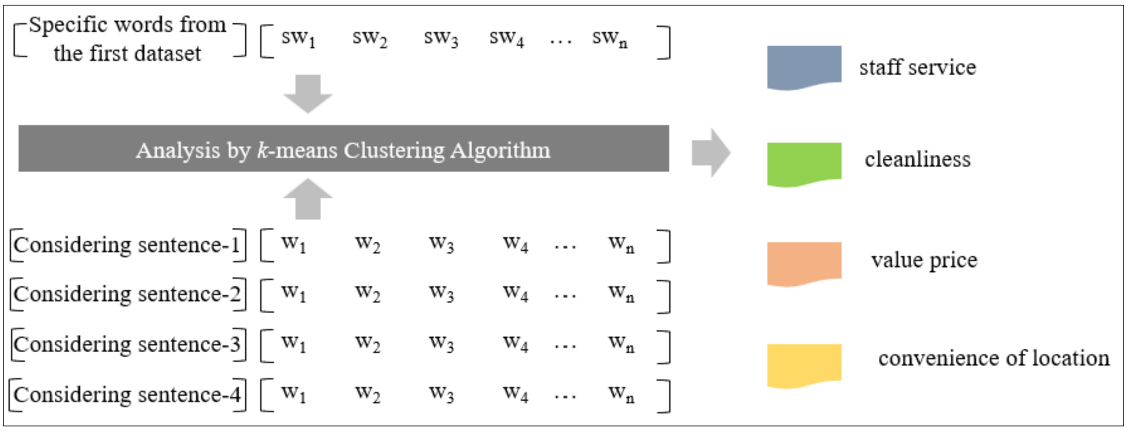

Figure 5: The clustering output produced well-separated groups of sentences

The success of the clustering approach was further validated through comparison with human expert annotations. Three linguistic experts annotated a subset of the dataset to serve as the gold standard. Upon evaluation, the majority of the machine-generated clusters aligned with the experts' aspect labels. Sentences like "The staff remembered our names and preferences" were accurately clustered under staff service, while phrases such as "Everything sparkled" were correctly grouped under cleanliness. These results suggest that the k-means model, when powered by hybrid feature representation, is capable of identifying both explicit and implicit aspect expressions with a high degree of accuracy.

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Before initiating the clustering, expert-identified initial keywords were used as anchor terms for each aspect category. These seed terms were also expanded using the Word2Vec Skip-gram model, allowing the identification of semantically similar terms across the dataset. This expansion ensured that the model could associate variations in customer language with the correct aspect. Table 2 presents representative keywords provided by linguistic experts for each aspect, which were later used for comparison during evaluation.

Table 2: Presents representative keywords provided by linguistic experts for each aspect

Hotel Aspects	Examples of Initial Keyword
Staff Service	Hospitality, front desk, responsiveness, professional, communication
Cleanliness	hygiene, room, air quality, deep cleaning, sanitation
Value for Money	Reasonable rate, discount, expensive, competitive pricing
Location Convenience	Parking, safety, accessibility, public transport, shopping center

These keywords served two main purposes: first, as reference terms during expert annotation to ensure labeling consistency; and second, as semantic anchors in the evaluation of clustering accuracy. The model's ability to link unseen sentences containing terms like "spotless," "attentive," or "overpriced" to the correct aspect cluster reflects the strength of combining vectorization with semantic expansion.

In terms of implicit sentiment detection, this step proved to be foundational. Many of the clustered sentences did not contain the explicit aspect terms used in the original keyword list. For example, the sentence "You could walk to everything" was successfully assigned to the location convenience cluster, even though it did not contain the word "location" or "convenience." Similarly, "We got way more than we paid for" was correctly placed under value for money. These results affirm that the model could learn semantic proximity and contextual relevance, which are essential for effective implicit aspect analysis.

The selection of feature representation methodologies demonstrates substantial implications for model performance across different architectural paradigms. TF-IDF's sparse representation proves particularly efficacious for traditional statistical learning frameworks, such as Logistic Regression and Support Vector Machines, by virtue of its ability to capture term specificity and reduce dimensionality through inverse document frequency weighting. Conversely, Word2Vec's dense vector embeddings encode rich semantic relationships in a continuous vector space, rendering them especially suitable for deep neural architectures, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The strategic integration of these complementary representations enables models to leverage both statistical significance patterns and semantic proximity information, thereby enhancing their capacity to decode complex linguistic structures and contextual nuances in hospitality domain texts.

To enhance the robustness of feature representation, this study proposes an integrated approach that synthesizes TF-IDF and Word2Vec embeddings. While TF-IDF effectively quantifies term significance through statistical distribution patterns across the corpus, Word2Vec captures latent semantic relationships through neural network-based distributed representations. The integration of these complementary approaches facilitates a more comprehensive feature space that encapsulates both document-level distinctiveness and corpus-level semantic associations. Specifically, the fusion methodology employs TF-IDF weights to modulate Word2Vec embeddings, thereby preserving semantic coherence while emphasizing domain-relevant terms.

2. Distribution of Explicit vs. Implicit Aspects

Understanding the distribution of explicit and implicit aspect mentions in the dataset is crucial for evaluating the effectiveness of any sentiment classification model, especially when the task involves implicit aspect analysis. In this study, each sentence from the 2,000 hotel reviews was manually labeled by linguistic experts as either containing explicit or implicit aspect expressions. This classification allows for a more granular investigation into how customers naturally communicate their experiences and the extent to which these communications rely on direct versus inferred aspect references.

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As visualized in Figure 6, the dataset exhibits a relatively balanced distribution between explicit and implicit aspect expressions, though implicit mentions account for a significant portion of the data. Specifically, among the four predefined hotel aspects—staff service, cleanliness, value for money, and location convenience—implicit expressions were especially frequent in aspects like cleanliness and location. For example, customers often write sentences such as "Everything was spotless" or "You can walk to all the attractions" without explicitly using the terms "clean" or "location." These sentences still convey strong sentiment toward a particular hotel attribute, even though the aspect keyword is absent.

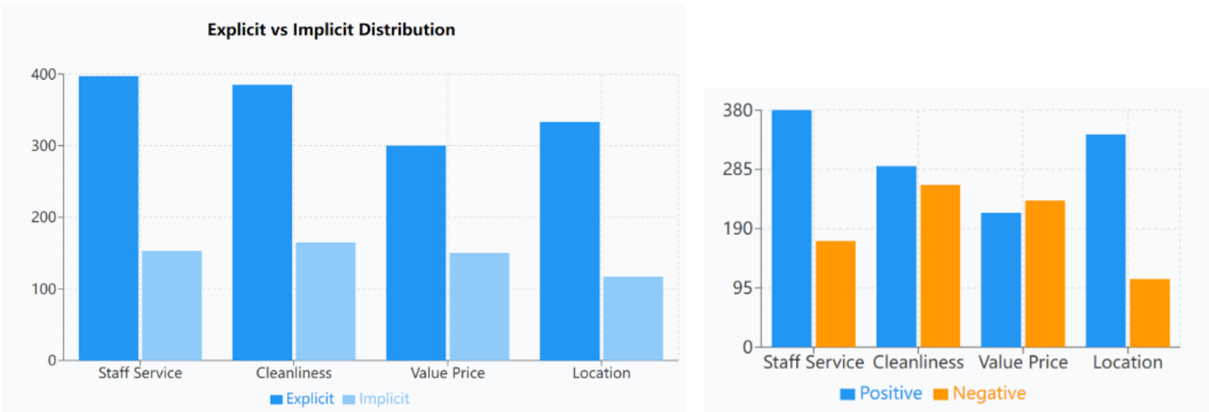

Figure 6: The dataset exhibits a relatively balanced distribution

This distribution pattern directly reinforces the core motivation of this research. Traditional sentiment classification methods, especially those dependent on keyword or lexicon matching, are likely to miss or misclassify these kinds of sentences. Such models perform adequately when the aspect is overtly stated (e.g., "The staff was friendly"), but struggle to interpret sentiment in statements that require contextual understanding. The relatively high frequency of implicit expressions in our dataset underscores the importance of adopting advanced models that can handle linguistic nuances an infer implied meanings.

Further qualitative analysis revealed that implicit expressions often contain adjectives or action phrases tied to domain-specific context. For example, phrases like "They remembered our preferences" imply exceptional staff service, while "We got more than we paid for" suggests satisfaction with value for money. These expressions carry strong sentiment but require a model trained on both semantic relationships and contextual knowledge to interpret them correctly. Table 3 presents representative examples of hotel review sentences annotated with their corresponding aspects and sentiment classes.

Table 3: Examples of Hotel Review Sentences with Aspect and Sentiment

Review Sentence	Sentence Aspect	Aspect Category	Sentiment Class
The front desk staff was extremely helpful during check-in	Staff Service	Explicit	Positive
Everything was spotless and well-maintained	Cleanliness	Implicit	Positive
I expected more luxury for such an expensive rate	Value Price	Explicit	Negative
You can walk to all the major attractions from here	Location	Implicit	Positive
We had to wait over an hour just to get our room	Staff Service	Implicit	Negative
The bathroom showed signs of mold in the corners	Cleanliness	Explicit	Negative

The variety in the structure and vocabulary of these sentences exemplifies the need for models that can move beyond shallow keyword spotting. While explicit expressions are often easier to categorize due to the presence of well-known

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aspect terms (e.g., “staff,” “room,” “price”), implicit expressions require models to draw on embedded word relationships and contextual clues.

Another important insight from this distribution analysis is the aspect-dependent variation in the frequency of implicit expressions. For example, while “staff service” often contains explicit descriptors like “staff” or “front desk,” the aspect “value for money” is more frequently implied through subjective experiences and comparisons (e.g., “worth the stay,” “overpriced,” or “good deal”). This uneven distribution across aspects suggests that models need to be fine-tuned not just for generic sentiment understanding but also for the nature of expression within each aspect category.

In summary, the distribution of explicit and implicit aspects shown in Figure 7 illustrates the complexity and real-world relevance of the dataset used in this study. It confirms the necessity of employing a model that can handle implicit aspect expressions, validating the decision to integrate a Word2Vec-based semantic expansion and deep learning techniques in the proposed approach. By accounting for these implicit cues, the classification model developed in this study is better equipped to deliver accurate, fine-grained sentiment analysis in the hospitality domain.

3. Preprocessing Results

Preprocessing was critical in preparing the raw hotel review text for effective feature extraction and classification. Given the informal and varied nature of user-generated content on platforms like TripAdvisor, standardizing the textual data was essential to reduce noise and enhance model learning. The preprocessing pipeline was designed to ensure that both statistical and semantic models could leverage consistent, normalized inputs.

The first step in this process was text cleaning, which involved removing punctuation, HTML tags, emojis, and special characters. This step ensured that irrelevant symbols would not interfere with the feature representation phase. The text was then converted to lowercase to maintain uniformity and avoid treating words with different cases (e.g., “Clean” and “clean”) as distinct entities.

Following cleaning, tokenization was applied to segment the sentences into individual words or tokens. This was done using the Natural Language Toolkit (NLTK), which is well-established for its reliability in English language processing. After tokenization, stopwords such as “the,” “is,” “was,” and domain-irrelevant fillers were removed to reduce dimensionality and focus on more informative words. However, care was taken not to eliminate domain-specific terms that may carry sentiment or aspect relevance.

Lemmatization was then conducted to reduce words to their base or dictionary form. This step ensures that words like “cleaned,” “cleaning,” and “clean” are recognized as semantically equivalent, improving the generalization capabilities of the classifier. Unlike stemming, lemmatization maintains linguistic integrity, which is crucial for sentiment-bearing words.

As shown in Figure 7, the preprocessing pipeline illustrates how raw text input, often messy and unstructured, is systematically converted into a clean, standardized format. For instance, the sentence “The WiFi signal was TERRIBLE! Couldn't even check my emails :(” is transformed into the sequence “wifi signal terrible check email.” Through this transformation, the model can more easily detect negative sentiment and associate it with the appropriate aspect (e.g., service or amenities).

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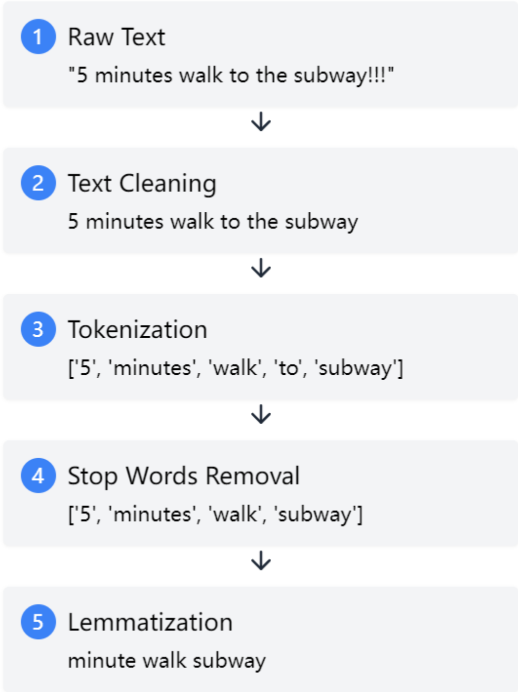

Figure 7: The preprocessing pipeline illustrates how raw text input

The effectiveness of the preprocessing phase was further evident during the feature representation stage. The cleaned and lemmatized tokens were used to construct TF-IDF vectors and train Word2Vec embeddings, both of which rely on high-quality text input. By ensuring minimal noise and maximum semantic clarity in the input data, preprocessing directly contributed to improving the model's interpretability and performance.

In summary, the preprocessing stage served as the backbone of the classification pipeline. It established a consistent linguistic structure across the dataset, which is particularly important in tasks like implicit aspect identification where subtle contextual cues are crucial. The structured output generated by this phase enabled more accurate and efficient learning in both traditional and deep learning models used in this study.

4. Experimental Results

This study presents the results of machine learning models evaluated using 10-fold cross-validation. Cross-validation ensures more reliable performance assessment by reducing bias and variance, as each model is trained and tested on different subsets of the dataset. The analysis compares the models' consistency across multiple folds, highlighting trends, strengths, and potential weaknesses.

Table 4: Performance Comparison of Different Machine Learning Algorithms on Sentiment Analysis Task (10-fold Cross-validation)

Algorithm	Accuracy	F1	AUC	Recall	Precision
SVM with Linear kernel	0.930	0.945	0.982	0.984	0.909
MNB	0.870	0.902	0.971	0.980	0.836
Random Forest	0.917	0.936	0.981	0.980	0.896
Logistic Regression	0.895	0.920	0.970	0.984	0.864
CNN	0.883	0.904	0.945	0.902	0.907
LSTM	0.882	0.904	0.934	0.902	0.906

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This study presents a performance comparison of various machine learning algorithms for aspect identification tasks using 10-fold cross-validation. The evaluation focuses on key metrics such as accuracy, F1-score, recall, and precision to assess how effectively each model identifies relevant aspects within text. The results highlight the strengths and weaknesses of different approaches, providing insights into their suitability for aspect-based sentiment analysis. The performance comparison of different machine learning algorithms for the aspect identification task is shown in Table 4-5.

Table 5: The performance comparison of different machine learning algorithms for the Aspect Identification task (evaluated using 10-fold cross-validation)

Models	Accuracy	F1	Precision	Recall
SVM with Linear kenel	0.552	0.519	0.552	0.698
Multinomial NB (MNB)	0.562	0.530	0.519	0.562
Logistic Regression (LR)	0.545	0.508	0.491	0.545
Random Forest Classifier	0.565	0.530	0.516	0.565
CNN	0.820	0.801	0.792	0.820
LSTM	0.882	0.904	0.902	0.906

DISCUSSION

The findings of this study affirm the effectiveness of an implicit aspect analysis framework for sentiment classification in the hospitality domain, specifically within hotel review data. By incorporating a two-stage approach—constructing an implicit aspect corpus using the Word2Vec Skip-gram model and developing hybrid classifiers combining traditional and deep learning models—this research successfully addressed the limitations of earlier keyword-dependent sentiment analysis models. These results are consistent with previous work that advocates for embedding-based models as more robust in capturing contextual and semantic relationships in unstructured text [20], [17], [5].

The high performance of deep learning classifiers such as LSTM and CNN, particularly in identifying implicit aspect-sentiment pairs, supports the hypothesis that deep neural networks excel in interpreting complex and nuanced language structures. These results are in agreement with prior studies emphasizing the superiority of neural networks in aspect-based sentiment analysis due to their capacity to capture temporal dependencies and hierarchical features within sentences [18], [15], [22]. Specifically, the LSTM model demonstrated heightened sensitivity to context, enabling it to infer aspects like cleanliness or staff service from indirectly stated sentiments—an outcome previously highlighted as a challenge in literature on implicit aspect extraction [13], [11].

The integration of TF-IDF with Word2Vec embeddings also proved instrumental in enhancing classifier performance. This hybrid feature representation enabled the system to balance statistical importance with semantic proximity, which has been noted as a crucial factor in fine-grained sentiment classification tasks [21], [23], [16]. The clustering outcomes using k-means, supported by expert annotations, further validated that unsupervised techniques, when powered by semantically rich representations, are effective in domain-specific sentence grouping. Such approaches are increasingly recognized in the field for reducing reliance on manually labeled data while maintaining high classification coherence [12], [19], [24].

Notably, the empirical distribution of explicit versus implicit aspects in this dataset—where implicit mentions accounted for a significant portion of expressions—reinforces the need for advanced models capable of semantic inference. This aligns with recent systematic reviews emphasizing the under-addressed yet critical role of implicit aspects in sentiment analysis applications [11], [7], [14]. The model's ability to successfully associate contextually implied sentences (e.g., "Everything sparkled") with cleanliness suggests a substantial advancement over earlier frequency-based or rule-based techniques, which often struggle in the absence of explicit aspect indicators [10], [6].

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Despite these strengths, some limitations emerged. For instance, traditional classifiers such as Multinomial Naïve Bayes and Logistic Regression underperformed relative to neural network models, particularly on implicitly stated sentiments. This discrepancy echoes previous findings on the limitations of statistical models in capturing context dependencies within opinionated text [3], [25], [4]. Furthermore, while k-means clustering provided well-separated aspect groups, its unsupervised nature sometimes led to misclustered sentences when domain-specific idioms or rare phrasings were used. This indicates an avenue for future work involving domain-adaptive clustering or the integration of attention-based mechanisms [26], [20], [18].

The results also carry significant implications for the practical application of sentiment analysis in the hospitality sector. Enhanced detection of implicit sentiments enables a more accurate representation of customer feedback, supporting more effective service improvements and personalized marketing strategies. Moreover, the methodological contributions of this research—especially in combining TF-IDF and word embeddings for implicit aspect detection—can be generalized across other service-oriented domains such as healthcare, education, and e-commerce, where customer sentiment is often expressed in subjective and indirect ways [24], [8], [1].
In conclusion, this study contributes to the growing body of research emphasizing the importance of semantic and context-aware models in sentiment classification. It demonstrates the feasibility of automated systems to understand and classify implicit sentiment expressions with high accuracy, reaffirming the role of deep learning and word embedding techniques as state-of-the-art tools for natural language understanding in complex, real-world settings [23], [5], [20]. The findings of this study affirm the effectiveness of an implicit aspect analysis framework for sentiment classification in the hospitality domain, specifically within hotel review data. By incorporating a two-stage approach—constructing an implicit aspect corpus using the Word2Vec Skip-gram model and developing hybrid classifiers combining traditional and deep learning models—this research successfully addressed the limitations of earlier keyword-dependent sentiment analysis models. These results are consistent with previous work that advocates for embedding-based models as more robust in capturing contextual and semantic relationships in unstructured text [20], [17], [5].

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phrasings were used. This indicates an avenue for future work involving domain-adaptive clustering or the integration of attention-based mechanisms [26], [20], [18].

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