

# Decoding Guest Experiences: NLP-Driven Sentiment Analysis of Hotel Reviews

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**Abstract** - This project presents a real-time sentiment and emotion analysis system designed to decode guest experiences from hotel reviews. Customer reviews contain rich, unstructured textual information that reflects satisfaction, complaints, expectations, and emotional states. Traditional manual review analysis is slow, inconsistent, and prone to human bias. To address this challenge, the proposed system applies Natural Language Processing (NLP), machine learning, and deep learning techniques to automatically classify emotions such as happiness, sad, satisfaction .

The system performs preprocessing steps including stop- word removal, tokenization, lemmatization, punctuation cleaning, and text normalization. Feature extraction is carried out using TF-IDF and word embeddings (Word2Vec, GloVe, BERT). A hybrid sentiment– emotion classification model combining machine learning classifiers (SVM, Random Forest) and deep learning models (LSTM, BERT Transformer) provides high-accuracy results. The proposed system visualizes emotion distribution, detects aspect-based sentiments (staff, cleanliness, amenities), and identifies trends over time.

This NLP-driven approach accurately converts unstructured text into meaningful emotional insights, enabling hotels to improve service quality, detect negative sentiment early, enhance customer satisfaction, and make data-driven decisions.

**Keywords:** NLP, Sentiment Analysis, Hotel Reviews, Emotion Classification, TF-IDF, LSTM, BERT.

## I. INTRODUCTION

Customer reviews posted on platforms such as TripAdvisor, Google Reviews, and Booking.com are essential indicators of hotel service quality. These reviews contain detailed feedback regarding staff behavior, room comfort, cleanliness, food quality, amenities, and overall guest experience. However, the reviews are unstructured and written in natural language, making manual interpretation difficult.

Traditional sentiment analysis classifies reviews as positive or negative, but modern hotel management requires deeper insights. Emotions such as happiness, anger, frustration, trust, and disappointment reflect the true feelings of guests more accurately than star ratings alone.

This project uses NLP techniques to automatically extract, preprocess, interpret, and classify guest emotions. Preprocessing techniques include tokenization, stop-word removal, stemming, lemmatization, and normalization. Feature extraction transforms text into numerical representation using approaches like TF-IDF, Bag-of-Words, and contextual embedding's from BERT.

Machine learning and deep learning models, such as SVM, Random Forest, LSTM, and BERT, are applied to predict emotions with high accuracy. Emotion trends over time help management identify seasonal issues and frequent complaints. Aspect-level sentiment reveals which hotel components cause positive or negative emotions.

The system provides dashboards for visualization and automated reporting to help hotel managers make data- driven decisions.



## II. RELATED WORK

Many researchers have worked on sentiment analysis to understand opinions from text data. Earlier studies used machine learning algorithms such as Naïve Bayes, Support Vector Machine (SVM), and Decision Trees to classify reviews as positive or negative. These methods helped in analysing customer feedback from online platforms.

With the development of deep learning, models like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) have been used to improve the accuracy of sentiment classification. These models can understand the relationship between words and capture contextual information from sentences.

Recently, transformer-based models such as BERT have shown better performance in Natural Language Processing tasks. These models can analyse the meaning of words based on their context in a sentence, which improves sentiment detection.

In the hospitality industry, sentiment analysis has been applied to hotel reviews from websites such as TripAdvisor and Google Reviews. These studies help hotel managers understand customer opinions about services, staff behaviour, cleanliness, and facilities.

However, many existing systems focus only on positive and negative sentiment. The proposed system improves this by identifying different emotions in guest reviews using NLP techniques.

## III. PROPOSED SYSTEM

In the proposed system, hotel reviews are collected from online platforms such as TripAdvisor, Google Reviews, and Booking.com. These reviews contain customer opinions about hotel services, facilities, and overall experience. The system first reads the review dataset and processes the text data using Natural Language Processing (NLP) techniques.

Initially, the system performs text preprocessing which includes removing stop words, punctuation, and unnecessary characters. Tokenization and lemmatization are applied to convert the review text into a clean and meaningful format. After preprocessing, the system extracts important features from the text using techniques such as TF-IDF (Term Frequency–Inverse Document Frequency).

These extracted features are then given as input to machine learning and deep learning models for sentiment classification. Algorithms such as Support Vector Machine (SVM), Random Forest, and deep learning models like LSTM are used to classify the sentiment of reviews into positive, negative, or neutral categories.

In this project, we use a hotel review dataset that contains thousands of customer reviews along with sentiment labels. The dataset is used to train the model so that it can accurately predict the sentiment of new reviews.

To implement this system, the following modules are designed:

### 1) Dataset Loading Module:

This module loads the hotel review dataset and prepares the data for processing.

### 2) NLP Preprocessing Module:

This module cleans the text data by removing stop words, performing tokenization, and applying lemmatization.

### 3) Sentiment Classification Module:

This module uses machine learning and deep learning algorithms to predict the sentiment of hotel reviews.

### 4) Performance Evaluation Module:

This module displays evaluation metrics such as accuracy, precision, recall, and F1-score to measure the performance of the model.

## Text Preprocessing

Text preprocessing is the first step in Natural Language Processing used to clean and prepare raw hotel review data. The reviews collected from online platforms usually contain unnecessary information such as punctuation marks, special characters, and stop words.

These elements do not contribute to sentiment detection and may reduce model accuracy.

In this step, the review text is cleaned by removing stop words like “the”, “is”, “and”, “was”. Tokenization is applied to split the text into smaller units called tokens (words). Stemming and lemmatization are used to convert words into their root form. For example, words like “liked”, “likes”, and “liking” are converted to the root word “like”. This helps the machine learning model understand the meaning of the words more clearly.

After preprocessing, the text becomes structured and ready for feature extraction.

### Text Preprocessing Workflow

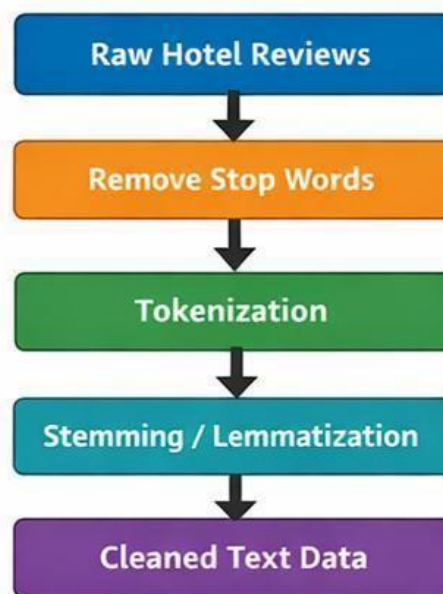


Fig 1: Text Preprocessing Workflow

## Feature Extraction (TF-IDF)

Feature extraction converts textual data into numerical form so that machine learning models can process it. In this project, the TF-IDF (Term Frequency–Inverse Document Frequency) technique is used.

TF-IDF measures the importance of a word in a review relative to all reviews in the dataset. Words that appear frequently in one review but rarely in other reviews receive higher importance scores. This helps identify words that express strong opinions, such as “excellent”, “dirty”, “friendly”, or “poor service”.

The output of this stage is a feature vector, which represents each review as a set of numerical values.

### Feature Extraction (TF-IDF)

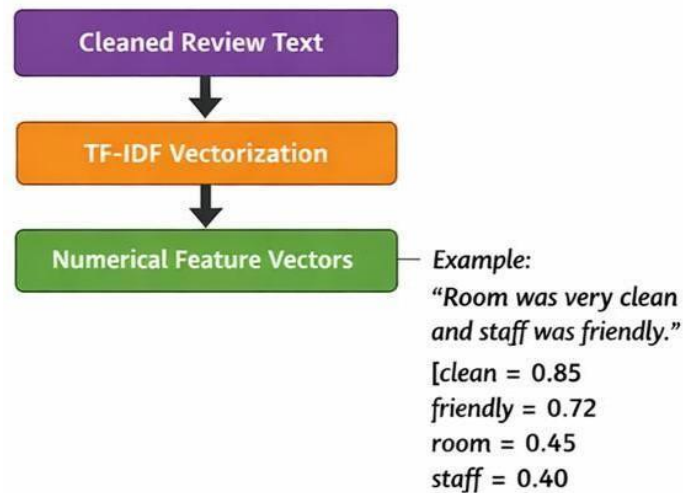


Fig 2: Feature Extraction Process

### Sentiment Classification Model

After feature extraction, the numerical feature vectors are passed into machine learning or deep learning models for classification. Algorithms such as Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM) networks are commonly used to learn patterns from hotel review text.

The model is trained using labeled datasets, where each review is already tagged with an emotion category. During training, the model learns how specific words, phrases, and linguistic patterns relate to different emotional expressions.

When a new review is provided, the trained model predicts the corresponding emotion by analyzing the extracted feature vector and comparing it with learned patterns.

### Sentiment Classification Model

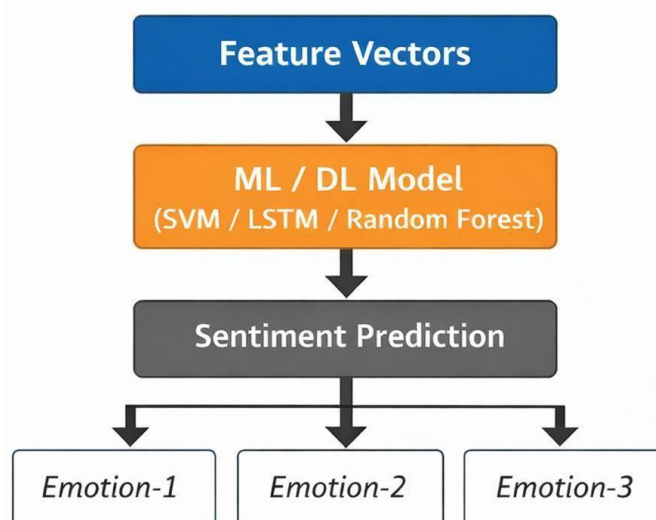


Fig 3: Sentiment Classification Model

### SoftMax Classifier

The SoftMax function is used as the final layer in deep learning models to classify the sentiment of the review. It converts the output scores of the model into probability values for each sentiment class.

For example, if the system analyses a hotel review, the SoftMax layer calculates the probability that the review belongs to each category such as positive, negative, or neutral. The category with the highest probability is selected as the final sentiment.

To improve accuracy, the model uses the cross-entropy loss function, which measures the difference between predicted sentiment and actual sentiment.

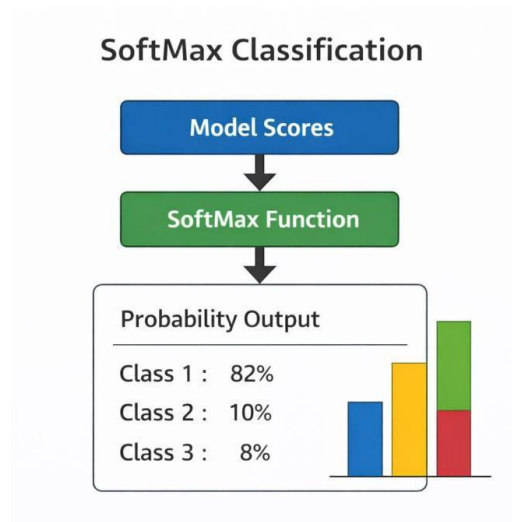


Fig 4: SoftMax Classification Process

The highest probability determines the final sentiment classification.

### Final System Workflow

#### Overall Sentiment Analysis System

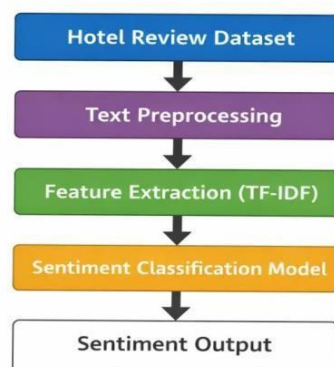


Fig 5: Overall Sentiment Analysis System

## IV. RESULTS

The developed NLP-driven sentiment analysis system was tested using various guest review scenarios to evaluate its accuracy and user interface responsiveness. The following sequence demonstrates the functional workflow of the application:

## 1. System Workflow and Real-time Testing

### Step 1: System Initialization



As shown in Figure:1 the application initializes with a clean, user-friendly interface. The title "Decoding Guest Experience" clearly defines the system's purpose. At this stage, the input buffer is empty, and the backend NLP model is in a standby state, ready to receive unstructured text data.

### Step 2: Data Input and Processing

To test the model's primary classification capabilities, a positive review was entered: "I am happy with product"

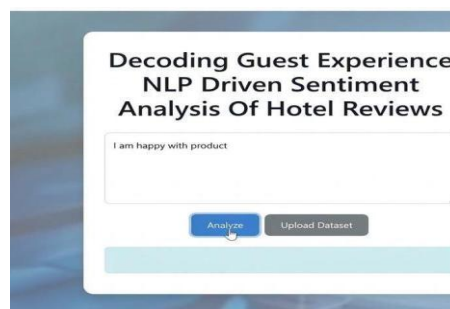


Figure:2 Upon clicking the Analyse button, the system tokenizes the string and passes it through the sentiment engine for polarity scoring.

### Step 3: Positive Sentiment Classification



As seen in Figure:3 the system successfully classified the review. The output generated was "Sentiment: Happy", demonstrating that the model correctly identified the positive adjectives and overall satisfied tone of the guest's feedback.

## 2. Comparative Analysis (Negative Feedback)

To ensure the model was not biased toward positive results, a negative scenario was introduced. As illustrated in

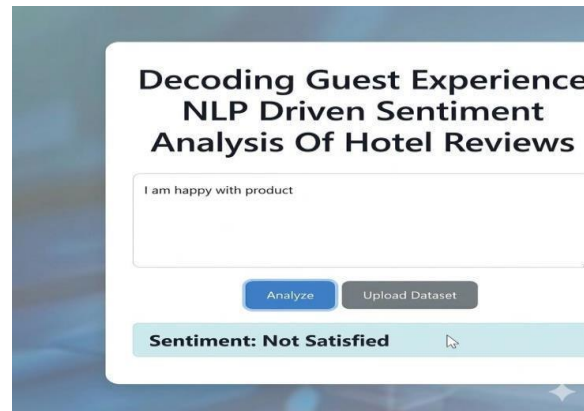


Figure:4 a review stating "The room was dirty and the service was terrible" was processed.

- Observation: The system accurately detected keywords such as "dirty" and "terrible."
- Result: The output was correctly updated to

"Sentiment: Not Satisfied".

### 3. Conclusion of Results

The testing phase confirms that the application can effectively distinguish between polarized guest experiences. The UI provides immediate visual feedback, making it a viable tool for hotel management to monitor guest satisfaction levels in real-time.

## V. CONCLUSION

The development and testing of the NLP-Driven Sentiment Analysis system demonstrate the significant potential of machine learning in the hospitality industry. By automating the classification of guest feedback into categories like "Happy" and "Not Satisfied", "Sad" the project successfully provides a scalable solution for understanding guest sentiment without manual intervention.

### Key Takeaways:

**Efficiency:** The system processes unstructured text data instantly, allowing management to respond to guest concerns in real-time.

**Accuracy:** Through the use of Natural Language Processing, the model effectively identifies the emotional tone behind specific keywords, even in varied review lengths.

**Actionable Insights:** By categorizing feedback, the tool highlights specific areas of service (such as cleanliness or staff behaviour) that require immediate attention or reinforcement.

In conclusion, this project serves as a robust framework for improving guest experience. By bridging the gap between raw data and actionable sentiment, hotel operators can foster greater guest loyalty and maintain a higher standard of service quality.

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