

# **Machine Learning Approach for Aspect-Based Sentiment Analysis on Bhubaneswar Hospitals Reviews**

Report

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## **Abstract**

The healthcare industry is increasingly relying on patient feedback to assess and improve service quality. In this study, we focus on the application of machine learning for Aspect-Based Sentiment Analysis (ABSA) on hospital reviews from Bhubaneswar, a rapidly growing city in India. The objective of this research is to dissect patient reviews and evaluate their sentiments across five critical aspects of hospital services: service quality, cleanliness, food, facilities, and staff behavior. For this purpose, we employ RoBERTa (A Robustly Optimized BERT Pretraining Approach), a state-of-the-art transformer-based Natural Language Processing (NLP) model, to accurately extract and categorize sentiments associated with these specific aspects from the user-generated textual reviews. Our methodology involves pre-processing raw reviews, aspect identification, sentiment classification, and score assignment. Each review is evaluated across the five chosen aspects, and sentiment scores are assigned on a scale, reflecting the patients' satisfaction levels for each aspect. These aspect-level sentiment scores are then compared with the overall review scores provided by the users, offering a comprehensive analysis of how well individual aspects align with the overall hospital ratings. This comparative analysis is expected to reveal significant patterns and discrepancies, thereby providing actionable insights into areas that contribute most to patient satisfaction, as well as those needing improvement. The results of this research can offer valuable implications for hospital administrators and policymakers, enabling them to better understand patient concerns and allocate resources more efficiently. Additionally, this work contributes to the growing field of sentiment analysis in healthcare by demonstrating the effectiveness of transformer-based models in understanding nuanced feedback.

# Introduction

In the healthcare industry, patient feedback plays a crucial role in shaping the quality of services and improving patient satisfaction. With the proliferation of online platforms like Google Maps and specialized healthcare review websites, patients now have the ability to share their experiences with hospitals and healthcare facilities more easily. These platforms offer a rich source of user-generated reviews, providing valuable insights into patient experiences. However, the widely used star rating system often fails to capture the depth and complexity of these reviews, offering only a general overview of patient satisfaction. This simplistic rating approach overlooks the diverse and nuanced opinions that patients may have regarding specific aspects of their hospital experiences, such as medical care, staff behaviour, hygiene, food quality, and facilities.

To address these limitations, Aspect-Based Sentiment Analysis (ABSA) has emerged as an effective method for extracting fine-grained opinions from user-generated content. ABSA enables us to identify and analyse sentiments related to specific aspects or features, offering a more detailed understanding of patient experiences. By applying ABSA to hospital reviews, it becomes possible to break down patient feedback into multiple dimensions, allowing healthcare providers and administrators to focus on targeted areas of improvement.

Recent advances in Natural Language Processing (NLP), particularly the development of transformer-based models like RoBERTa (Robustly Optimized BERT Pretraining Approach), have significantly improved the performance of sentiment analysis tasks. RoBERTa has proven to be highly effective in understanding the subtleties of human language, making it an ideal candidate for ABSA. By leveraging RoBERTa's powerful language understanding capabilities, we aim to extract specific sentiment information from hospital reviews, categorizing feedback into distinct aspects such as service quality, cleanliness, food, staff behaviour, and facilities. This enables us to assign sentiment scores to each aspect, providing a clearer and more accurate reflection of patient satisfaction.

Our project aims to build an advanced sentiment analysis framework that evaluates hospital reviews in Bhubaneswar, India. The key objectives include:

1. **Data Collection and Preprocessing:** We will scrape hospital reviews from publicly available platforms like Google Maps, clean the raw data, and prepare it for sentiment analysis.
2. **Aspect Identification:** Through a structured approach, we will identify key aspects of hospital services that are frequently mentioned in reviews, such as service quality, cleanliness, staff behavior, food, and facilities.
3. **Sentiment Analysis:** Using RoBERTa, we will perform aspect-specific sentiment analysis to determine the polarity (positive, negative, or neutral) of feedback for each aspect.
4. **Score Aggregation and Comparison:** Aspect-level sentiment scores will be aggregated to produce an overall sentiment score for each hospital. These scores will

then be compared with the star ratings to examine discrepancies and validate the robustness of the sentiment analysis.

5. **Evaluation and Future Enhancements:** The effectiveness of our approach will be evaluated, and future enhancements such as incorporating LSTM-based models or exploring hybrid deep learning techniques will be explored to improve the accuracy and comprehensiveness of aspect extraction and sentiment classification.

By developing this advanced ABSA model, we aim to offer a more nuanced and granular view of hospital performance, moving beyond traditional, simplistic evaluation systems like star ratings. Our model has the potential to empower hospital administrators by providing them with actionable insights into specific aspects of their services, such as the efficiency of their staff, the cleanliness of their facilities, and the quality of their food and amenities. This enables a more targeted approach to service improvement, allowing healthcare providers to address precise issues that may negatively affect patient satisfaction. Moreover, this aspect-based feedback can help hospitals prioritize resource allocation and focus on the areas that contribute most to overall patient experience and satisfaction.

Ultimately, our work seeks to bridge the gap between traditional star ratings—which often fail to capture the complexity of patient experiences—and the more intricate, multi-faceted nature of healthcare feedback. By breaking down reviews into distinct aspects, we aim to build a comprehensive understanding of patient sentiment, offering both hospitals and patients a more transparent, fair, and detailed evaluation framework. This not only enhances the quality of hospital services but also sets a precedent for how sentiment analysis can be applied to various other domains in the healthcare sector, providing a blueprint for future research and development in patient feedback systems.

## Literature Survey

Aspect-based sentiment analysis (ABSA) has become an increasingly significant research area in natural language processing (NLP), especially with the rise of user-generated content across various domains. ABSA focuses on identifying specific aspects within text and classifying the sentiment related to each aspect. In recent years, ABSA has been applied to various industries, including healthcare, where patient feedback is invaluable for improving service quality. The evolution of ABSA techniques from lexicon-based approaches to sophisticated deep learning models has enabled more accurate extraction and classification of sentiments from unstructured text data.

Early ABSA methods were grounded in lexicon-based approaches, which relied heavily on predefined sentiment lexicons and simple frequency-based techniques. One of the pioneering works in this field was by Hu and Liu (2004), who introduced a lexicon-based ABSA model that identified frequent noun phrases as aspects and classified sentiments based on a sentiment lexicon. While effective in identifying broad sentiments, these early methods struggled with contextual understanding and the nuanced expression of opinions, especially in complex domains like healthcare.

In the healthcare context, lexicon-based methods were applied to analyze patient feedback. For example, Doing-Harris et al. (2017) used frequent noun phrases and lexicons to identify aspects such as care quality, interpersonal communication, and technical competence in patient reviews. Though useful in extracting general sentiments, lexicon-based methods were limited in their ability to capture the complexity of natural language, often failing to account for sentiment shifts within sentences and the contextual relationship between different aspects.

With the advent of deep learning, ABSA techniques experienced a significant shift. Models based on Long Short-Term Memory (LSTM) networks became popular for sentiment analysis due to their ability to capture long-range dependencies in text and process sequential data effectively. Tang et al. (2016) introduced an LSTM-based model that jointly performed aspect extraction and sentiment classification, making it a more holistic approach to ABSA. This model leveraged the sequential nature of LSTM to better capture relationships between words and aspects in a sentence.

Building on the success of LSTMs, Wang et al. (2016) proposed an attention-based LSTM model to enhance ABSA tasks. The attention mechanism allowed the model to focus on the most relevant parts of the sentence concerning a specific aspect, improving sentiment classification accuracy. Attention mechanisms were particularly useful in addressing the issue of irrelevant information in sentences that might confuse the model's sentiment prediction.

The arrival of transformer-based models, particularly BERT (Bidirectional Encoder Representations from Transformers) by Devlin et al. (2019), marked a major breakthrough in NLP tasks, including ABSA. BERT introduced a bidirectional attention mechanism that allowed the model to consider the context of words from both the left and right, making it more powerful in capturing context-dependent meaning. Pre-training on vast amounts of text data, followed by fine-tuning on specific tasks, made BERT highly adaptable to a wide range of NLP challenges. Sun et al. (2019) adapted BERT for ABSA by constructing auxiliary sentences and

converting ABSA into a sentence-pair classification task. This method improved sentiment classification performance significantly, particularly in domains with complex language like healthcare.

Building upon BERT, RoBERTa (Robustly Optimized BERT Pretraining Approach) was introduced by Liu et al. (2019), further enhancing the capabilities of transformer models. RoBERTa modified key hyperparameters, used larger mini-batches, and increased training data, which resulted in stronger performance across various NLP benchmarks. RoBERTa's improved architecture made it highly suitable for ABSA tasks, especially in domains where the context and nuances of language are crucial for sentiment analysis.

In healthcare-specific applications, Gao et al. (2019) utilized BERT for aspect-based sentiment analysis on drug reviews, showcasing improved performance over traditional machine learning methods. Their work demonstrated the effectiveness of using large, pre-trained models like BERT for domain-specific ABSA tasks. Similarly, Xu et al. (2019) fine-tuned BERT for aspect-based sentiment classification, achieving better results than LSTM-based models, further validating the shift toward transformer models in ABSA research.

For hospital reviews, Ranard et al. (2016) conducted an analysis of Yelp hospital reviews to identify key themes such as staff professionalism and facility cleanliness. While not strictly an ABSA approach, their work highlighted the value of mining online reviews for insights into patient experiences. This paved the way for more focused ABSA techniques to be applied in the healthcare domain, where sentiment related to specific aspects could provide actionable insights for hospital administrators.

Looking ahead, advancements in ABSA are likely to involve even more sophisticated deep learning techniques. The integration of Graph Neural Networks (GNNs) with LSTM and attention mechanisms is being explored to capture the complex relationships between aspects and sentiments. These advancements will enable more fine-grained analysis of patient feedback, providing deeper insights into the interaction between various aspects of healthcare services and patient satisfaction.

Our research builds on the advancements made in ABSA by leveraging the power of RoBERTa, a state-of-the-art transformer model, to perform aspect-based sentiment analysis on hospital reviews. We aim to adapt RoBERTa to the specific context of hospital reviews, focusing on key aspects such as service, cleanliness, food, facilities, and staff. Additionally, we will aggregate aspect-level sentiment scores into an overall score for each hospital and compare these with the existing star ratings to validate the effectiveness of our model.

The novelty of our approach lies in:

1. **Applying RoBERTa to the healthcare domain** by analyzing hospital reviews for aspect-specific sentiments, an area that has seen limited exploration compared to other industries.
2. **Developing a method to aggregate aspect-level sentiment scores** into an overall sentiment score that can be compared with star ratings, offering a more nuanced evaluation of hospital performance.

3. **Building an end-to-end pipeline** that includes web scraping, data preprocessing, aspect extraction, sentiment analysis, and validation, providing a comprehensive system for analyzing patient feedback.
4. **Exploring future advancements** by incorporating LSTM networks and other deep learning techniques to enhance sentiment classification accuracy and robustness.

By leveraging the advancements in NLP and deep learning, particularly RoBERTa, our research aims to offer a more sophisticated and reliable approach to understanding patient satisfaction in hospitals. This work not only contributes to the field of sentiment analysis but also provides valuable insights for healthcare administrators to improve service quality and patient care.

# Proposed Solution

Our proposed solution for Aspect-Based Sentiment Analysis (ABSA) on hospital reviews involves a comprehensive pipeline consisting of several key components. Each stage plays a crucial role in ensuring that we accurately extract, analyze, and interpret sentiments from patient feedback. By employing advanced NLP models like RoBERTa, and integrating future enhancements using LSTM and deep learning techniques, we aim to provide a robust system for understanding patient experiences.

## 1. Data Collection and Preprocessing

Data collection and preprocessing are the foundational steps of our solution. The goal is to gather hospital reviews and prepare them for further analysis.

- **Data Collection:**
  - We will collect hospital reviews from publicly available platforms such as Google Maps, Yelp, and specialized healthcare review sites. The collection will be performed using web scraping techniques, which involve extracting text data from websites using automated scripts. APIs (Application Programming Interfaces) will also be utilized where available to ensure efficient data retrieval.
  - The data will include user reviews, star ratings, timestamps, and metadata related to hospital services. This raw data will serve as the input for further analysis.
- **Preprocessing:**
  - **Data Cleaning:** The raw reviews will undergo preprocessing to remove any noisy data such as duplicates, irrelevant content (e.g., advertisements or promotional text), and special characters. The text will be normalized by converting it to lowercase, removing stopwords (common words that do not contribute to sentiment), and applying stemming or lemmatization to reduce words to their root forms.
  - **Aspect Definition:** We will manually define key aspects relevant to hospital services, such as service quality, food, staff behavior, facilities, and hygiene. These categories will guide the aspect extraction process.
  - **Text Normalization:** Sentences with slang, abbreviations, or incorrect grammar will be standardized to ensure consistency in the reviews. This step is vital to improve the accuracy of subsequent analysis steps.

## 2. Aspect Identification

Aspect identification is crucial to ABSA, as it involves identifying specific parts of the review that correspond to different aspects of hospital services.



- **Manual Aspect Definition:** In this stage, we will define aspect categories that are relevant to hospital reviews. These may include categories like service, cleanliness, food quality, staff friendliness, and facilities. The manual aspect definition ensures that the categories align with patient expectations and hospital services.
- **Aspect Extraction:**
  - **Rule-Based Methods:** Rule-based methods involve manually defining linguistic patterns (rules) to identify sentences or phrases related to specific aspects. For example, sentences mentioning "cleanliness" or "hygiene" could be tagged as related to hygiene.
  - **NLP Techniques:** To enhance aspect extraction, we will use NLP techniques such as Named Entity Recognition (NER) or Part-of-Speech (POS) tagging to automatically extract aspect-related terms. By identifying nouns and noun phrases, the system can classify sentences into appropriate aspects.

### 3. RoBERTa-Based Sentiment Analysis

RoBERTa (Robustly Optimized BERT Pretraining Approach) is a state-of-the-art transformer model, and it will be central to our sentiment analysis process.

- **RoBERTa Overview:** RoBERTa builds upon BERT (Bidirectional Encoder Representations from Transformers), which is known for its ability to understand the context of words in a sentence. RoBERTa improves upon BERT by optimizing hyperparameters, training with larger mini-batches, and using more extensive pre-training data. These improvements make RoBERTa one of the best models for NLP tasks, especially for sentiment analysis.
- **Sentiment Classification:** Using RoBERTa, we will classify each aspect-related sentence into sentiment categories: positive, negative, or neutral. This classification is crucial because it helps us understand how patients feel about specific aspects of the hospital experience.
- **Fine-Tuning:** We will fine-tune RoBERTa on a labeled dataset of hospital reviews. Fine-tuning is the process of adjusting the model parameters to perform well on a specific task—in this case, sentiment analysis of hospital reviews. By training RoBERTa on domain-specific data, we can improve its ability to correctly classify sentiments in hospital-related contexts.

### 4. Score Aggregation

Once sentiment analysis has been performed on each aspect, the next step is to aggregate the sentiments into an overall score.

- **Aspect-Level Sentiment Aggregation:** For each hospital, we will combine the sentiment scores of all the identified aspects. Each aspect will contribute to an overall

sentiment score. The aggregation will consider the polarity (positive, negative, or neutral) and intensity of sentiments expressed in the reviews.

- **Weighting of Aspects:** Not all aspects have the same importance to patients. For instance, service quality may carry more weight than food quality when evaluating a hospital. To reflect this, we will apply weighting factors to each aspect based on its frequency and importance in the reviews. This weighted approach will help produce a more accurate overall sentiment score.

## 5. Validation and Comparison

Validation is essential to ensure that our ABSA model produces reliable and accurate sentiment scores.

- **Comparison with Existing Ratings:** We will compare the aggregated sentiment scores generated by our model with the existing star ratings provided by patients on review platforms. By doing this, we can identify any discrepancies between overall ratings and aspect-based sentiment scores. This comparison will help us assess whether our model captures nuanced patient opinions that are missed by simple star ratings.
- **Model Evaluation:** We will use evaluation metrics like accuracy, precision, recall, and F1-score to validate the performance of our sentiment classification model. These metrics will provide insights into how well the model performs in identifying and classifying sentiments for each aspect.

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## 6. Future Enhancements: Integration of LSTM and Deep Learning Techniques

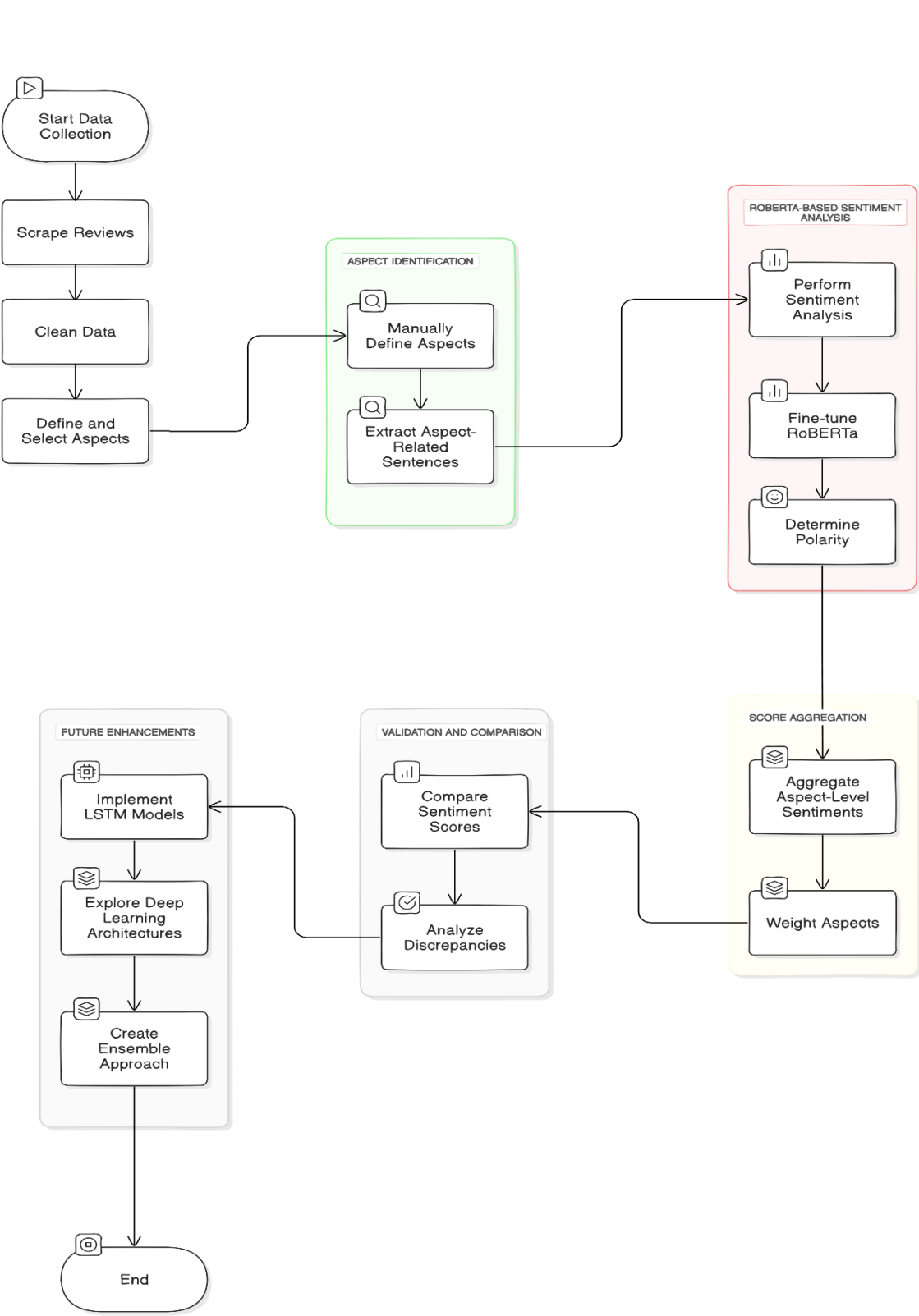
To further improve the robustness and accuracy of our ABSA system, we plan to explore several advanced deep learning techniques in future iterations.

- **LSTM-Based Models:** Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that can capture temporal dependencies in sequences. For sentiment analysis, LSTMs can be useful in understanding long-term context within reviews, especially when sentiments evolve over the course of a sentence or paragraph. We plan to incorporate LSTM-based models to enhance sentiment classification by capturing the sequential flow of information.
- **Attention Mechanisms:** Attention mechanisms allow the model to focus on the most relevant parts of the input text. We will integrate attention-based models to improve aspect extraction and sentiment analysis. Attention helps in assigning higher importance to critical words or phrases in a review, enabling more accurate classification.
- **Graph Neural Networks (GNNs):** GNNs are a class of deep learning models that excel at capturing relationships between different entities. In ABSA, GNNs can be used to model the relationships between different aspects of a hospital and their associated sentiments. By incorporating GNNs, we aim to better capture the interplay between various aspects of hospital services and patient satisfaction.

- **Ensemble Learning:** We will explore the use of ensemble models, which combine multiple models (e.g., RoBERTa, LSTM, and attention mechanisms) to improve overall performance. By leveraging the strengths of different models, we can create a more robust and accurate ABSA system.

By combining state-of-the-art NLP techniques, such as RoBERTa, with future enhancements like LSTM and advanced deep learning methods, our proposed solution aims to provide a more granular and accurate analysis of hospital reviews. This will allow for more informed decision-making by hospital administrators and offer prospective patients a more detailed understanding of hospital performance across different aspects.

# Block Diagram



**Fig 1:** Advanced Sentiment Analysis Framework for Hospital Reviews

## Results and Discussion

To evaluate the effectiveness of our proposed Aspect-Based Sentiment Analysis (ABSA) model, we will conduct a thorough analysis using the collected dataset of hospital reviews. This evaluation will focus on both quantitative and qualitative metrics to assess how well the model performs in extracting and analyzing sentiments for different aspects of hospital services. By breaking down the overall ratings into more specific categories such as service quality, cleanliness, food, staff behavior, and facilities, our goal is to provide a more granular understanding of patient satisfaction.

Title	Hospital Rating	Review Stars	Aspect Scores
Vivekanand Hospital Bhubaneswar	4.6	5	{'service': 0.12956, 'cleanliness': 0.19434, 'food': 0.06478, 'facilities': 0.12956, 'staff': 0.12956}
Health Village Hospital	4.6	3	{'service': -0.19454000000000002, 'cleanliness': -0.29181, 'food': -0.09727000000000001, 'facilities': -0.19454000000000002, 'staff': -0.19454000000000002}
Manipal Hospitals, Bhubaneswar	4.6	1	{'service': -0.1756, 'cleanliness': -0.26339999999999997, 'food': -0.0878, 'facilities': -0.1756, 'staff': -0.1756}
Sunshine Hospital	4.6	5	{'service': 0.19424, 'cleanliness': 0.29135999999999995, 'food': 0.09712, 'facilities': 0.19424, 'staff': 0.19424}

### Key Metrics for Evaluation

#### 1. Sentiment Classification Accuracy for Each Aspect

- **Definition:** Sentiment classification accuracy refers to the model's ability to correctly identify the sentiment (positive, negative, or neutral) for each aspect of the hospital review. For instance, if a patient mentions "the staff was very friendly," the model should classify this sentence as positive for the staff behavior aspect.
- **Measurement:** We will use standard evaluation metrics such as accuracy, precision, recall, and F1-score to quantify how well the model performs in sentiment classification for each aspect. These metrics will be calculated separately for each aspect to give a detailed view of the model's performance.
  - **Accuracy** measures the overall percentage of correct sentiment predictions (both positive and negative).
  - **Precision** refers to the proportion of true positive classifications (correct positive predictions) out of all the positive predictions the model makes.
  - **Recall** calculates the proportion of true positive classifications out of all actual positive instances in the data.

- **F1-score** provides a balance between precision and recall, especially useful when dealing with imbalanced datasets where one sentiment (e.g., positive) might dominate.
- **Importance:** High accuracy in sentiment classification for each aspect ensures that the model captures the nuances of patient feedback, thereby providing useful insights into specific strengths and weaknesses of the hospital.

## 2. Correlation Between Generated Overall Sentiment Scores and Existing Hospital Ratings

- **Definition:** Correlation measures the relationship between two variables. In our case, we will evaluate the correlation between the sentiment scores generated by our ABSA model and the existing overall hospital ratings (e.g., star ratings). A high correlation would indicate that our model's sentiment scores align well with the existing ratings, suggesting that it accurately reflects patient satisfaction as captured by current methods.
- **Measurement:** We will calculate the Pearson or Spearman correlation coefficient to quantify the degree of association between the sentiment scores generated from aspect-level analysis and the existing hospital ratings.
  - **Pearson Correlation** is used to measure the linear relationship between two continuous variables.
  - **Spearman Correlation** is a non-parametric measure that assesses how well the relationship between two variables can be described using a monotonic function.
- **Importance:** This metric is crucial to validate the reliability of our model. By comparing our aspect-based scores with overall ratings, we can determine if the model is accurately capturing the general sentiment or whether it reveals discrepancies that simple star ratings might overlook.

## 3. Qualitative Analysis of Aspect-Level Insights

- **Definition:** Qualitative analysis involves manually examining specific examples of reviews to understand the model's strengths and weaknesses in classifying sentiments and identifying aspects. While quantitative metrics provide overall performance statistics, qualitative analysis allows us to look deeper into how well the model understands real-world data.
- **Measurement:** We will conduct a detailed examination of selected reviews, focusing on how well the model identifies sentiments across different aspects. For example, we will analyze whether the model correctly identifies sentiment for nuanced feedback, such as when a patient provides mixed opinions (e.g., "The doctors were great, but the waiting time was too long").
- **Importance:** This type of analysis helps us understand whether the model is able to provide meaningful and actionable insights. It can also highlight areas where the model struggles, such as with complex sentences or implicit sentiments, and guide future improvements.

## Conclusion

Our Aspect-Based Sentiment Analysis (ABSA) model offers a more detailed and insightful understanding of patient reviews compared to traditional star ratings. By analyzing specific aspects like service, staff behavior, cleanliness, facilities, and food quality, we provide hospital administrators with actionable feedback to identify strengths and areas needing improvement. This aspect-level insight gives a clearer picture of patient experiences, addressing the limitations of generalized ratings that may overlook critical details.

For patients, the model provides greater transparency and more reliable information when choosing a healthcare facility. It empowers individuals to make better-informed decisions based on detailed reviews that align with their personal priorities, such as the quality of care or hygiene standards. The correlation between our sentiment scores and overall ratings ensures that the analysis is both robust and trustworthy, revealing discrepancies and offering deeper insights.

By leveraging RoBERTa, a state-of-the-art pre-trained NLP model, our solution highlights the power of transformer-based architectures in understanding complex sentiments within domain-specific data. Looking ahead, the integration of advanced techniques like LSTM and attention mechanisms will further enhance sentiment classification accuracy and aspect extraction, making our ABSA model a valuable tool for improving patient satisfaction and hospital transparency.

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