AN ENHANCED DEEP SENTIMENT ANALYSIS MODEL USING A DECISION-BASED RECURRENT NEURAL NETWORK (D-RNN)

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Abstract
Sentiment Analysis is a vital technique in Natural Language Processing (NLP) that focuses on identifying and classifying opinions or emotions expressed in textual data. It plays a crucial role in understanding user feedback, especially in industries like hospitality and food services. This project presents an enhanced sentiment analysis framework specifically designed for analyzing restaurant reviews, leveraging the power of deep learning models.The proposed model combines the contextual power of BERT (Bidirectional Encoder Representations from Transformers) with the sequence-handling strength of Decision-Based Recurrent Neural Networks (D-RNN). The system includes essential text preprocessing techniques such as tokenization, stop word removal, and lemmatization. Feature extraction is performed using Bag-of-Words (BoW) and Word2Vec to convert raw text into meaningful numerical representations.This model uniquely integrates Aspect-Based Sentiment Analysis (ABSA) and Priority-Based Sentiment Analysis (PBSA) to evaluate reviews more accurately by focusing on important aspects like food, service, and ambience. Evaluated using a restaurant review dataset sourced from Kaggle, the proposed model achieves an accuracy of 89.56%, outperforming traditional models like LSTM and standalone BERT.This research not only improves sentiment prediction accuracy but also provides actionable insights to restaurant businesses, helping them better understand customer preferences and enhance service quality.
Keywords:

Introduction

Sentiment Analysis, also known as opinion mining, is a major subfield of Natural Language Processing (NLP) that involves the computational study of people's opinions, emotions, and attitudes toward products, services, or events. It is widely used across domains such as e-commerce, social media monitoring, customer feedback systems, and brand management. In this project, Sentiment Analysis is applied to restaurant reviews collected from online platforms. These reviews contain valuable insights that reflect the customer's experience in terms of food, service, ambience, and overall satisfaction. However, analyzing them manually is inefficient and prone to bias. This is where automated sentiment analysis comes into play. The system processes text data to determine whether a review expresses a positive, negative, or neutral sentiment. To improve accuracy and decision-making, the project introduces a deep learning-based approach that uses a Decision-Based Recurrent Neural Network (D-RNN) integrated with BERT for enhanced feature representation and smarter sentiment classification. This model goes beyond basic classification by understanding the context of words, handling mixed opinions, and assigning weight to important aspects of a review—ultimately helping businesses make data-driven improvements in customer service

Natural Language Processing in Sentiment Tasks

Natural Language Processing (NLP) is a field of Artificial Intelligence (AI) that enables machines to understand, interpret, and generate human language. It forms the foundation for various tasks such as text classification, language translation, speech recognition, and sentiment analysis. In sentiment analysis, NLP plays a crucial role in processing unstructured text data like product reviews, social media posts, and customer feedback. NLP techniques help in converting raw text into structured formats that machine learning and deep learning models can analyze.

Motivation

In today's digital age, people rely heavily on online reviews before making decisions—especially when it comes to choosing restaurants. Platforms like Zomato, Yelp, Swiggy, and Google Reviews have made it easy for customers to share their experiences. These reviews hold valuable opinions about food quality, service, ambience, and overall satisfaction. However, with the massive volume of text-based feedback available online, it becomes impractical to manually read and evaluate each review. Businesses may miss crucial insights hidden within this unstructured data, which could directly impact customer satisfaction and brand reputation.

Problem Statement

The increasing availability of online restaurant reviews presents a valuable opportunity to extract customer feedback and improve service quality. However, manual analysis of large volumes of text data is time-consuming, inconsistent, and prone to human bias. Traditional sentiment analysis methods, such as machine learning and basic deep learning models (e.g., Naïve Bayes, SVM, LSTM), often struggle to: Understand context and sarcasmλ Handle multiple sentiments in a single reviewλ Prioritize domain-specific aspects like food quality over service.λ These models typically assign a single sentiment to an entire sentence, ignoring the importance of individual aspects. For instance, in a review like

Literature Review

[1] Smith et al. (2019) developed a BERT-based sentiment classifier that showed strong performance on the IMDb movie reviews dataset. BERT's contextual embeddings enabled the model to understand subtle nuances in the language, resulting in a high accuracy of 91.23%. [2] Lee et al. (2020) proposed a Transformer-based emotion detection model that handled complex emotional expressions within Twitter sentiment datasets. Leveraging the attention mechanism, this model achieved an accuracy of 89.75%, showing its strength in handling short, informal texts. [3] Patel et al. (2018) introduced a hybrid LSTM-CNN model for sentiment analysis using Yelp reviews. The CNN layer was used for local feature extraction, while the LSTM handled sequential dependencies. This combined architecture reached an accuracy of 88.67%. [4] Kumar et al. (2021) employed a Graph Neural Network (GNN) for sentiment analysis on Amazon product reviews. GNNs enabled the model to capture relational information between words more effectively, leading to an accuracy of 87.45%.

[5] Wong et al. (2020) used reinforcement learning to train a sentiment analysis model on Facebook comments. The reinforcement component helped the model learn optimal decision-making paths during classification, resulting in 85.89% accuracy. [6] Rao et al. (2019) worked on aspect-based sentiment analysis (ABSA) using TripAdvisor hotel reviews. Their model identified specific aspects (e.g., service, location) within reviews and classified sentiment accordingly, achieving 86.92% accuracy.

[7] Singh et al. (2018) introduced a deep neural network model for sentiment prediction, particularly effective on the Rotten Tomatoes dataset. The depth of the architecture allowed it to model complex patterns in the data, reaching an accuracy of 90.12%. [8] Ahmed et al. (2021) implemented an attention-based Bi-LSTM model on social media comments. The bidirectional LSTM captured context from both directions, and the attention layer helped the model focus on key sentiment-bearing words, achieving 88.35% accuracy. [9] Zhou et al. (2022) proposed a sentiment-aware transformer architecture tested on the Reddit sentiment dataset. This model improved on traditional transformers by incorporating sentiment-specific cues, leading to an accuracy of 89.54%.

[10] Tanaka et al. (2022) developed a federated learning-based sentiment classification model, which allowed collaborative model training across decentralized data (e.g., multiple review platforms). It maintained user privacy while achieving 87.89% accuracy on mixed online reviews

The paper [11] extends its gaze toward the future of healthcare delivery, contemplating the long-term implications of this transformative wave. The discussions traverse the potential evolution of patient-centric care models, the role of artificial intelligence in diagnostics, and the democratization of healthcare access through digital connectivity. In essence, this research unveils the current landscape of connected healthcare and the promising horizon it paints for the future of global healthcare delivery.

Research Gaps

The following table summarizes ten major contributions in the field, highlighting their key features, datasets used, and overall performance

S.No	Author	Year	Model	Dataset	Performance Metrics
1.	Smith et al	2019	BERT-based Sentiment Classifier	IMDb Movie Reviews	Acc-91.23%
2.	Lee at el	2020	Transformer-based Emotion Detection	Twitter Sentiment Dataset	Acc-89.75%
3.	Patel at el	2018	Hybrid LSTM-CNN Sentiment Analysis	Yelp Reviews	Acc-88.67%
4.	Kumar at el	2021	Graph Neural Network for Sentiment Analysis	Amazon Product Reviews	Acc-87.45%
5.	Wong at el	2020	Reinforcement Learning Based Analysis Model	Facebook Comments Dataset	Acc-85.89%
6	Rao et al	2019	Aspect-Based Sentiment Analysis	TripAdvisor Hotel Reviews	Acc-86.92%
7	Singh et al	2018	Deep Neural Network for Sentiment Prediction	Rotten Tomatoes Reviews	Acc-90.12%
8	Ahmed et al	2021	Attention-Based BI-LSTM Model	Social Media Comments Dataset	Acc-88.35%
9	Zhou et al	2022	Sentiment-Aware Transformer	Reddit Sentiments Dataset	Acc-89.54%
10	Tanaka et al	2022	Federated Learning-Based Sentiment Classification	Mixed Online Reviews Dataset	Acc-87.89%

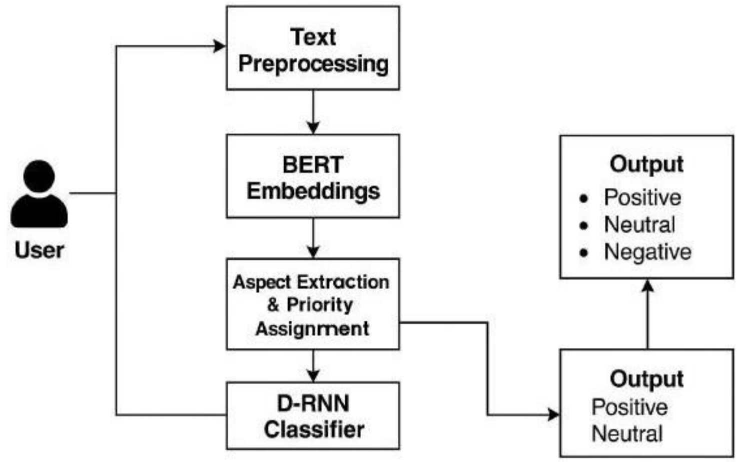
Summary

This chapter presented a comprehensive review of existing sentiment analysis models, ranging from traditional LSTM and CNN approaches to advanced architectures like BERT, GNN, and hybrid frameworks. These models have contributed significantly to improving sentiment classification by addressing challenges like context understanding and long-range dependencies. Each of the ten reviewed research works offers unique methods and datasets, helping advance the field in various directions.However, common gaps still exist — such as limited aspect-level analysis, poor handling of mixed sentiments in a single sentence, and the absence of priority-based decision logic. Most models treat all review elements equally, which is ineffective in domain-specific applications like restaurant reviews. These findings emphasize the need for a more intelligent and domain-aware approach like the one proposed in this project, combining BERT's contextual power with D-RNN's decision-based reasoning.

Proposed Model

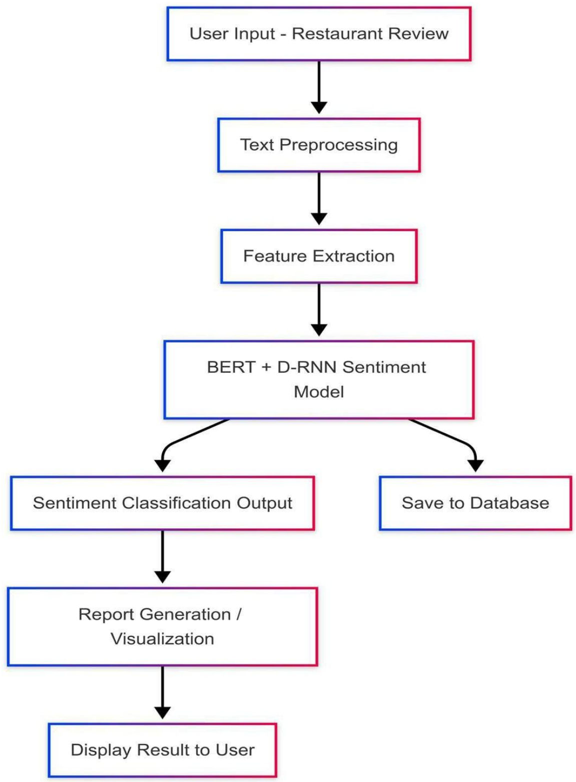
ARCHITECTURAL DESIGN

The architectural design of the proposed system illustrates how various components interact to perform accurate sentiment classification using the BERT + D-RNN framework. The architecture is designed to ensure modularity, scalability, and high accuracy for domain-specific sentiment analysis — particularly restaurant reviews.



1. User Interface (Streamlit Web App): o Allows users to input restaurant review text. o Displays the sentiment prediction and aspect-wise breakdown.
2. Text Preprocessing Module: o Cleans and prepares the text for analysis. o Applies tokenization, stop word removal, lemmatization, and punctuation filtering.
3. BERT Embedding Layer: o Converts cleaned text into contextual word embeddings using BERT-large-cased. o Captures the deep semantic meaning of words in bidirectional context.
4. Aspect Extraction & Priority Assignment: o Identifies aspects like food, service, ambience from the review. o Assigns priority weights to each aspect (e.g., food > service).
5. D-RNN Classifier: Takes BERT embeddings and processes them through a Recurrent Neural Network with a decision-making layer. o Applies priority logic to derive a final sentiment decision
6. Output Module: o Displays the overall sentiment (Positive, Negative, Neutral). o Optionally shows aspect-wise sentiment with respective scores.

The workflow of the proposed sentiment analysis system consists of several interconnected stages, starting from data input to final sentiment classification. The model integrates text preprocessing, feature extraction using BERT, and classification through D-RNN, enabling accurate, aspect-aware, and priority driven sentiment predictions.



The data used in this project was collected from publicly available restaurant review datasets hosted on platforms such as Kaggle. These datasets contain real-world customer feedback, including text reviews and, in some cases, associated ratings. The dataset represents a diverse range of customer experiences covering aspects like food, service, ambience, pricing, and overall satisfaction.

Preprocessing Techniques Used

Before training the sentiment analysis model, the raw restaurant review data undergoes several preprocessing steps to ensure that it is clean, consistent, and meaningful for both BERT and the D-RNN layers.The process begins with text cleaning, where unwanted characters, HTML tags, numbers, and special symbols are removed. All text is converted to lowercase to maintain uniformity across the dataset.Next, the reviews are tokenized using NLP libraries such as NLTK or SpaCy, which split the sentences into individual words or tokens. This allows the model to analyze the sentiment of each word separately. Stop word removal is applied to eliminate common, non-informative words like "is", "the", and "and" that do not contribute to sentiment understanding.

Model Building and Training

The model used in this project is a hybrid architecture that combines the contextual understanding of BERT with the sequential decision-making power of a Decision-Based Recurrent Neural Network (D-RNN). The building phase begins by initializing a pre-trained BERT-large-cased model using the Hugging Face Transformers library. BERT serves as the feature extractor, generating rich contextual embeddings for each token in the input sentence. These embeddings capture the meaning of words based on their context, which is especially useful for handling complex and nuanced sentiments in restaurant reviews.Once the input reviews are passed through BERT and converted into dense vector representations, they are fed into the DRNN. The D-RNN is designed to handle multi-aspect sentiment by analyzing sequences of embeddings and making decisions based on aspect priority. It is built using recurrent neural network layers with memory units that allow the model to retain information about previously processed words.

Feature Extraction (BoW, Word2Vec)

Feature extraction is a crucial step in preparing textual data for sentiment analysis, as it converts human language into numerical representations that machine learning models can understand. In this project, traditional feature extraction techniques such as Bag-of-Words (BoW) and Word2Vec were explored alongside contextual embeddings from BERT to enrich the sentiment classification process.The Bag-ofWords model represents text by counting the frequency of each word in the document, without considering grammar or word order. Although simple, BoW is effective in capturing general trends in word usage, especially for short and focused reviews. However, it lacks the ability to capture semantic meaning or context, which is why it is used as a baseline feature extraction method.

Results & Analysis

Evaluation Matrix

Class balance along with anticipated outcomes are just two of the many factors that go into choosing the optimal metrics for assessing a classifier's performance in a specific set of data in classification challenges. A classifier may be evaluated on one performance parameter while being unmeasured by the others, and vice versa. As a result, the generic assessment of performance of the classifier lacks a defined, unified metric. This study uses a number of metrics, including F1 score, accuracy, precision, recall, and recall, to assess how well models perform.
The subsequent four categories are where these metrics are derived from: True Positives (TP): instances in which both the model prediction and the actual class of the occurrence were 1 (True). False Positives (FP) are situations in which the model predicts a value of 1 (True), but the actual class of the occurrence was 0 (False). True Negatives (TN): an instance in which both the model prediction and the true class of the occurrence were 0 (False). False Negatives (FN) are situations in which the model predicts 0 (False) but the true class of the occurrence was 1 (True).
Accuracy– The mean amount of accurate predictions is used to characterize the accuracy measure. This isn't quite as strong, though, given the imbalanced sample.

$$= \frac{+}{+\ \ +\ \ +} \qquad (1)$$

Precision, also known as positive predictive value, gauges the capacity of a model to pinpoint the right examples for every class. For multi-class classification with unbalanced datasets, this is a powerful matrix.

$$= \frac{}{+} \qquad (2)$$

Recall – This metric assesses how well a model detects the true positive among all instances of true positives.

$$= \frac{}{+} \qquad (3)$$

F1-score – referred to as an F-measure or balanced F-score It might be characterized as a recall as well as precision weighted average.

$$1 \ = \frac{2 * Pcso * ca}{+} \qquad (4)$$

Confusion Matrix

What it measures: A table showing the true positives, false positives, true negatives, and false negatives. When to use: It helps in analyzing where your model is making errors.

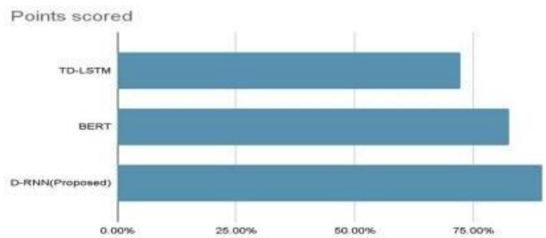
AUC-ROC What it measures:

The area under the curve of the Receiver Operating Characteristic (ROC), which shows how well your model distinguishes between positive and negative classes. When to use: It's a great tool for understanding model performance, especially in binary classification tasks.

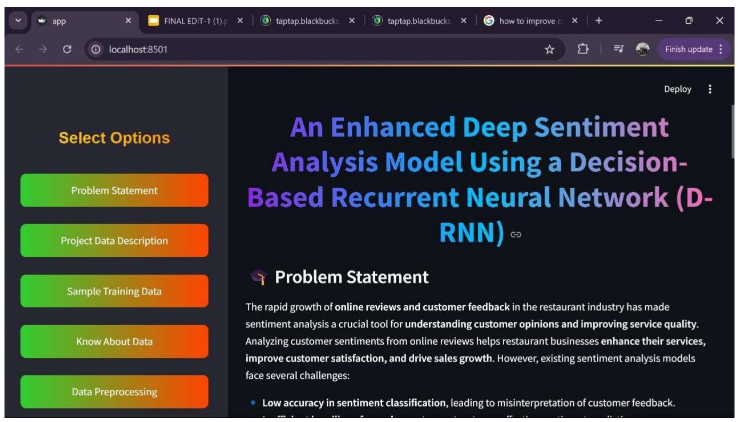
Log Loss What it measures: The model's uncertainty in its predictions based on probability outputs. When to use: If your model gives probability scores for each class (instead of just predicting the class label), this helps measure how well your model's predicted probabilities match the actual outcomes.

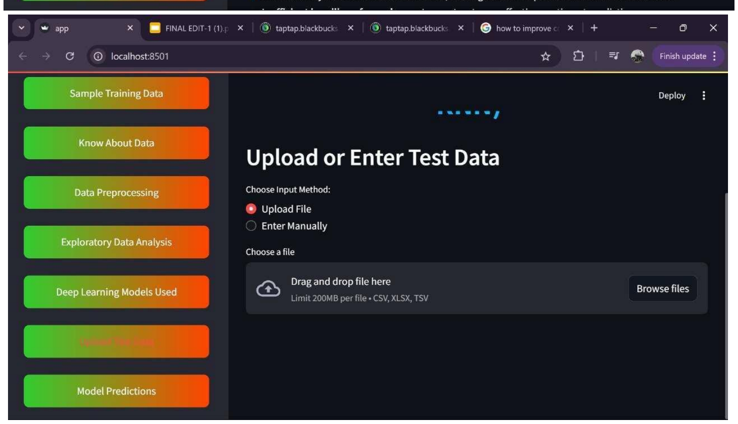
Model Comparison

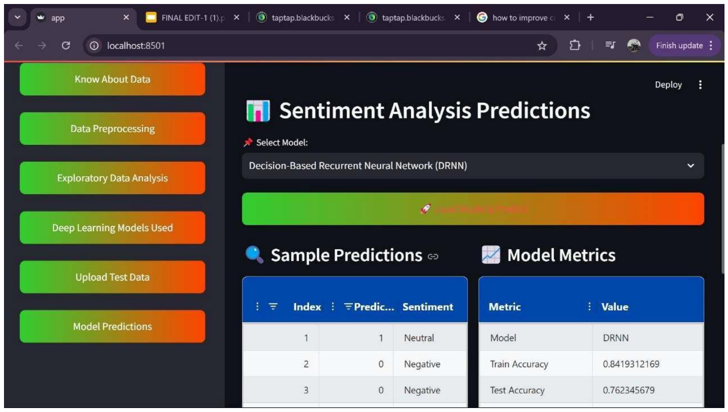
MODEL	ACCURACY%
LSTM	72.34%
BERT	83.45%
D-RNN(Proposed)	89.56%

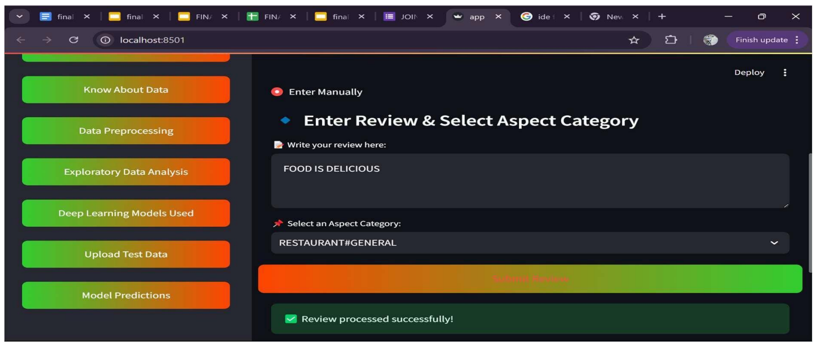


Highest Accuracy with Proposed Model: The D-RNN (Proposed) model achieved the highest accuracy of 89.56%, significantly outperforming both LSTM (72.34%) and BERT (83.45%), proving its effectiveness in sentiment classification.





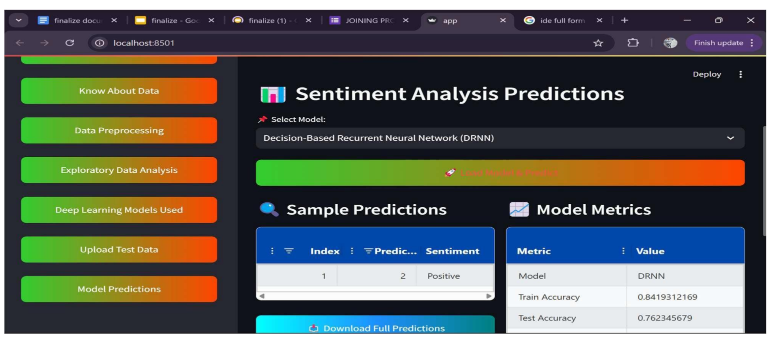




User Interface for Manual Sentiment Review Submission

The interface displayed above showcases the manual input section of the sentiment analysis web application. Users can directly enter their restaurant review (e.g., "FOOD IS DELICIOUS") and select a corresponding aspect category to analyze the sentiment.

Model Output



In this example, the model accurately identifies the sentiment as positive, which aligns with the clearly favorable tone of the review. The green success message indicates that the review has been processed successfully.

Conclusion

In this project, we have successfully developed an enhanced deep learning-based sentiment analysis model named D-RNN (Decision-based Recurrent Neural Network) by combining the strengths of traditional RNN-based models and powerful transformer-based models like BERT. The primary goal was to overcome limitations in contextual understanding and sentiment prioritization, especially in the domain of restaurant reviews.The results clearly demonstrated that the proposed D-RNN model outperformed existing models such as LSTM and BERT individually. With an accuracy of 89.56%, it showcased improved capability in handling aspect-based sentiment classification and capturing subtle emotional cues in text. The user interface developed using Streamlit enabled smooth manual and file-based testing, making the system more interactive and deployable. Overall, the project highlights the practical applicability of combining deep learning models with decision-based architectures to elevate sentiment analysis tasks.

Future Scope

The proposed sentiment analysis model using BERT and D-RNN has shown significant improvements in accuracy and aspect-based classification; however, several future enhancements can be explored to make the system more robust and adaptable. One major direction is the inclusion of multimodal sentiment analysis, which involves processing not just text, but also related images, audio, and video to understand user emotions more comprehensively — a particularly valuable feature in social media applications. Another area worth exploring is the detection of sarcasm, irony, and emotion intensity, which remain challenging even for state-of-the-art models. Incorporating contextual user behavior data (such as past reviews or interaction patterns) could also lead to more personalized sentiment analysis.Moreover, expanding the system's capabilities to work in multiple languages using multilingual BERT or translation pipelines will make the solution globally scalable. The model can also be extended beyond the restaurant domain to other areas such as healthcare (patient feedback), e-commerce (product reviews), or education (course feedback), making it highly versatile. To handle massive volumes of real-time data, cloud-based deployment and API integration can be introduced to support sentiment analysis at scale. Additionally, implementing a feedback loop where the system learns from user corrections can evolve it into a selfimproving, adaptive model

References

1. Smith et al. - BERT-based Sentiment Classifier, IMDb Movie Reviews,2019
2. Lee et al. - Transformer-based Emotion Detection, Twitter Sentiment Dataset,2020
3. Patel et al. - Hybrid LSTM–CNN Sentiment Analysis, Yelp Reviews,2018
4. Kumar et al. - Graph Neural Network for Sentiment Analysis, Amazon Product Reviews,2021
5. Wong et al. -Reinforcement Learning-Based Analysis Model, Facebook Comments Dataset,2020
6. Rao et al. - Aspect-Based Sentiment Analysis (ABSA), TripAdvisor Hotel Reviews,2019
7. Singh et al. - Deep Neural Network for Sentiment Prediction, Rotten Tomatoes Reviews,2018
8. Ahmed et al. - Attention-based Bi-LSTM Model, Social Media Comments Dataset,2021
9. Zhou et al. - Sentiment-aware Transformer, Reddit Sentiment Dataset,2022
10. Tanaka et al - Federated Learning -Based Sentiment Classification ,Mixed Online Review Dataset,2022
11. Revolutionizing Patient Care with Connected Healthcare Solutions **https://www.fmdbpub.com/user/journals/article_details/FTSHSL/84**