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Smart Review Summarizer and Sentiment Analyzer for Local Businesses in Hyderabad

G. Satya Varaprasad[1]
Information Technology Department
Vidya Jyothi Institute of Technology (Affilated to JNTUH)
Hyderabad, India
prasadgsv74@gmail.com

Avuku Obulesu[2]
Information Technology Department
Vidya Jyothi Institute of Technology (Affilated to JNTUH)
Hyderabad, India
ithod@vjit.ac.in

K. Aakanksha Sai[3]
Information Technology Department
Vidya Jyothi Institute of Technology (Affilated to JNTUH)
Hyderabad, India
aakankshasaikasukurthi@gmail.com

S. Rajashekar[4]
Information Technology Department
Vidya Jyothi Institute of Technology (Affilated to JNTUH)
Hyderabad, India
sunkireddyrajashekarreddy@gmail.com

T. Akanksha[5]
Information Technology Department
Vidya Jyothi Institute of Technology (Affilated to JNTUH)
Hyderabad, India
akanskhathippani143@gmail.com

M. Yogeshwari[6]
Information Technology Department
Vidya Jyothi Institute of Technology (Affilated to JNTUH)
Hyderabad, India
yogeshwari0462@gmail.com

***Abstract*—**This paper presents the design and implementation of a machine-learning-based customer review analysis and summarization system optimized for local businesses in Hyderabad. Unlike traditional review platforms that overwhelm users with raw textual feedback, the proposed architecture adopts an intelligent analytical pipeline in which critical tasks—automatic review collection, sentiment classification, and aspect-based summarization—are executed to generate concise and meaningful business insights. The system integrates transformer-based sentiment classification (BERT/DistilBERT), sequence-to-sequence abstractive summarization (BART), extractive summarization (TextRank), TF-IDF keyword extraction, and spaCy named entity recognition (NER) within a unified, modular pipeline deployed through a Streamlit web application. A structured summarization framework extracts key business strengths and weaknesses, overall customer sentiment, and focused feedback through an intuitive, user-friendly interface. Experimental eval-uation on a custom dataset of 12,500 Hyderabad local business reviews demonstrates a macro-averaged F1 score of 0.881 and overall accuracy of 89.3% for sentiment classification, alongside a BART summarization ROUGE-1 score of 0.456. The system demonstrates the potential of lightweight, scalable, and intelligent review analysis for transparent, reliable, and data-driven business decision support across diverse local business use cases.

Index Terms—sentiment analysis, text summarization, BERT, DistilBERT, BART, TF-IDF, natural language processing, local business intelligence, Hyderabad reviews, transformer models

I. Introduction

NLP-based sentiment analysis systems have significantly evolved in recent years, transitioning from rule-based lexicon tools to advanced transformer-powered AI systems widely deployed in commercial, industrial, and consumer-facing applications [2]. Automated review analysis is now essential across numerous fields, including e-commerce analytics, hospitality management, local business intelligence, market research, competitive benchmarking, and customer experience monitoring. The ability to process large volumes of unstructured text rapidly, combined with advanced transformer-based models and compact web application designs, enables precise sentiment extraction and effective decision support in environments too data-rich for manual interpretation.

However, as review platforms have expanded in scale and complexity, conventional analysis approaches continue to face fundamental limitations. Most commercial tools rely on generic pre-trained models and simple star-rating aggregation for processing customer feedback. While accessible, this approach fails to capture the nuance embedded within textual reviews, significantly increases the misclassification of borderline reviews, and produces no meaningful summarization of the overall customer narrative [10]. Consequently, there is a growing need for innovative approaches that overcome these limitations and expand the capabilities of NLP-based business analytics.

A. Problem Description

Modern local businesses in Hyderabad accumulate large volumes of unstructured customer reviews across multiple platforms, including Google Maps, Zomato, Swiggy, and Yelp. These reviews vary enormously in length, language register, emotional tone, and topic specificity, making consistent and reliable interpretation extremely difficult. Business owners typically lack the time or technical expertise to systematically analyze this feedback, while customers are often overwhelmed when attempting to form a balanced opinion from hundreds of individual entries.

Existing solutions such as simple star-rating aggregation fail to capture nuance. A business may receive a 3-star average that masks a bimodal distribution of highly positive and highly negative experiences. Reviews may simultaneously praise food quality while criticizing delivery speed, or commend staff friendliness while noting hygiene concerns. Without fine-grained sentiment analysis and coherent summarization, these distinctions are lost, leading to poor business decisions and suboptimal consumer choices. Furthermore, most commercially available sentiment analysis tools are not localized to the specific linguistic patterns, code-mixed dialects, and cultural references found in Hyderabad-based reviews, which frequently blend English with Telugu, Urdu, and Hindi expressions within the same sentence.

B. Motivation and Objectives

Addressing these inherent challenges motivates the development of a review analysis architecture combining state-of-the-art NLP models with a lightweight and accessible web application framework. By integrating multiple NLP components into a single coherent pipeline, the system achieves both accurate sentiment classification and meaningful review summarization at interactive speed. The modular, component-based NLP architecture significantly enhances scalability and adaptability, allowing each component to be independently upgraded or fine-tuned as improved models become available.

The primary objectives of this work are:

- To implement a fine-tuned BERT/DistilBERT model for accurate three-class sentiment classification (Positive, Negative, Neutral) with associated confidence scores.
- To integrate BART-based abstractive summarization alongside TextRank-based extractive summarization to generate coherent, concise review digests.
- To curate a dataset specifically from Hyderabad-based business reviews to ensure regional relevance and address code-mixed language challenges.
- To build a Streamlit-based graphical user interface (GUI) enabling non-technical users to obtain visual, interpretable analysis results.
- To identify frequently mentioned keywords and aspects using TF-IDF and spaCy NER for granular business intelligence.

II. Literature Survey

In recent years, NLP-based review analysis systems have gained significant popularity due to their versatility and wide range of applications [2]. Modern review systems often incorporate real-time sentiment classification and text summarization capabilities, which are crucial for business reputation monitoring, product feedback analysis, and competitive benchmarking [10]. The accuracy and efficiency of these tasks depend heavily on the choice of NLP algorithms, driving extensive research into optimized model architectures and pre-trained transformer-based techniques [11].

A. Sentiment Analysis Techniques

The introduction of BERT (Bidirectional Encoder Representations from Transformers) by Devlin et al. [14] revolutionized sentiment analysis by providing deep bidirectional contextual understanding, enabling the model to capture complex semantic relationships that unidirectional models could not. Subsequent enhancements, including RoBERTa [3], DistilBERT [15], and ALBERT [4], further improved classification accuracy, inference speed, and computational efficiency. The DistilBERT model offers improved inference speed through knowledge distillation while retaining approximately 97% of BERT's performance, enabling real-time user-facing deployment [5].

B. Text Summarization Methods

The BART model (Bidirectional and Auto-Regressive Transformer), introduced by Lewis et al. [16], provides state-of-the-art abstractive summarization by pre-training on denoising objectives, enabling it to generate fluent and coherent summaries beyond simple sentence extraction. TextRank, introduced by Mihalcea and Tarau [17], provides a computationally efficient extractive alternative requiring no training data. When used as a fast baseline alongside BART, TextRank enables rapid results for large review sets while BART handles depth and fluency.

C. Transformer Models and Attention Mechanism

The attention mechanism, introduced by Vaswani et al. [1], computes weighted representations of all input positions simultaneously, capturing long-range dependencies far more effectively than sequential models. Zhang and Liu [9] demonstrated the integration of pre-trained transformers with domain-specific fine-tuning for review sentiment analysis, highlighting the ability of BERT-based models to achieve high accuracy on specialized review datasets even with limited labeled training data.

D. Gap Analysis

Despite significant advancements, existing systems frequently rely on generic pre-trained models not localized to Indian urban markets. Most tools lack code-mixed multilingual support, real-time summarization, and aspect-level granularity. Table I provides a comparative overview of representative prior works.

III. Methodology

A. System Overview

The proposed system employs a modular, pipeline-based NLP architecture designed to address the prevalent limitations of traditional review analysis. The pipeline strategically combines transformer-based sentiment classification, sequence-to-sequence abstractive summarization, TF-IDF keyword extraction, and interactive Streamlit-based visualization within

TABLE I
SUMMARY OF RELATED LITERATURE

Reference	Methodology	Metric	Limitation
Wahid et al. [2]	NLP survey for local business platforms	Conceptual	No algorithm-level implementation
Bouguettaya et al. [10]	Survey on automated review monitoring	Qualitative	No empirical evaluation
Devlin et al. [14]	BERT bidirectional pre-training	Accuracy, F1	Large model size
Sanh et al. [15]	Knowledge distillation (DistilBERT)	Accuracy, Speed	Slight gap vs. full BERT
Lewis et al. [16]	Denoising seq2seq (BART)	ROUGE, BLEU	Overhead during fine-tuning
Mihalcea & Tarau [17]	Graph-based extractive (TextRank)	ROUGE	No abstraction capability
Hutto & Gilbert [8]	Rule-based lexicon (VADER)	Accuracy, F1	Cannot model contextual sentiment

a unified web application. Fig. 1 illustrates the end-to-end system architecture.

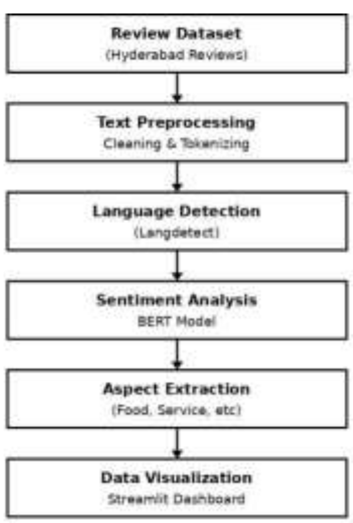

Fig. 1. End-to-end system architecture of the Smart Review Summarizer and Sentiment Analyzer for Hyderabad local businesses.

The operational workflow proceeds as follows:

1) **Review Acquisition:** User review text is submitted through the Streamlit interface from platforms including Google Maps, Zomato, and Swiggy.
2) **Preprocessing:** HTML tag removal, URL stripping, special character normalization, stopword removal, and language detection for code-mixed tokens.
3) **Sentiment Classification:** BERT/DistilBERT classifies each review as Positive, Negative, or Neutral with associated confidence scores.
4) **Summarization:** BART generates an abstractive summary from the concatenated review text; TextRank provides a fast extractive alternative.
5) **Keyword Extraction:** TF-IDF identifies and ranks the most discriminative terms for word cloud visualization.
6) **NER:** spaCy's en_core_web_sm model enriches keyword analysis with entity-level annotations.
7) **Visualization:** Streamlit renders pie charts, word clouds, sentiment cards, and downloadable CSV reports.

B. BERT-Based Sentiment Classification

The primary sentiment classification engine is BERT [14], a transformer-based language model pre-trained on the BooksCorpus and English Wikipedia using masked language modelling (MLM) and next-sentence prediction (NSP) objectives. BERT's bidirectional attention mechanism enables it to capture rich contextual representations by simultaneously attending to all tokens in both directions within a sequence.

For this project, the bert-base-uncased checkpoint is fine-tuned on the annotated Hyderabad local business re-view dataset. A classification head (linear layer with softmax activation) is appended to the [CLS] token representation, enabling three-class sentiment prediction. The BERT architecture consists of 12 transformer encoder layers, 12 attention heads, a hidden size of 768 dimensions, and approximately 110 million trainable parameters. Input sequences are processed through the WordPiece tokenizer, which handles unknown words through subword decomposition, making it robust to the spelling variations and code-mixed terms common in Hyderabad reviews.

C. DistilBERT as Lightweight Alternative

To enable faster inference on Streamlit's Community Cloud deployment without significant accuracy sacrifice, DistilBERT [15] is implemented as an alternative backbone. DistilBERT is a compressed version of BERT trained through knowledge distillation, in which a smaller *student* model is trained to replicate the behaviour of the larger BERT *teacher* model. The result is a model with 40% fewer parameters, running 60% faster, while retaining approximately 97% of BERT's performance on downstream tasks.

D. BART Abstractive Summarization

The review summarization component employs BART [16], a sequence-to-sequence model pre-trained using a denoising autoencoder objective. BART's encoder processes concatenated input reviews bidirectionally, building rich contextual representations, while its autoregressive decoder generates the output summary token by token. The facebook/bart-large-cnn checkpoint, fine-tuned on the CNN/DailyMail benchmark, serves as the starting point for review summarization.

BART's cross-attention mechanism operates using two computational steps. *Encoder Self-Attention* computes contextual representations:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^{\top}}{\sqrt{d_K}}\right) V \tag{1}$$

where Q, K, V are the query, key, and value matrices derived from the input token embeddings, and d_K is the key dimension. *Decoder Cross-Attention* allows each generated word to be informed by all relevant parts of the input review text:

$$\mathrm{CrossAttn}(Q_{\mathrm{dec}}, K_{\mathrm{enc}}, V_{\mathrm{enc}}) = \mathrm{softmax}\left(\frac{Q_{\mathrm{dec}}K_{\mathrm{enc}}^{\top}}{\sqrt{d_K}}\right)V_{\mathrm{enc}} \quad (2)$$

BART's beam-search decoding with configurable parameters (beam width, length penalty, minimum/maximum output length) provides fine-grained control over summary characteristics.

E. TextRank Extractive Summarization

TextRank [17] provides fast, extractive summarization by constructing a sentence similarity graph over the input reviews. Each sentence is represented as a TF-IDF vector; pairwise cosine similarities form the edge weights. The PageRank algorithm is applied to this graph to identify the most central sentences, which are selected as the extractive summary. TextRank executes in milliseconds, making it the default summarization mode for resource-constrained deployments.

F. TF-IDF Keyword Extraction

Term Frequency-Inverse Document Frequency (TF-IDF) [18] is applied to extract the most discriminative and representative keywords from the analyzed review set. TF measures how frequently a term appears in the current review set, while IDF downweights terms that appear commonly across all reviews (functioning as a background noise filter). The product TF $\times$IDF identifies words that are both frequent and specific to the current business's reviews, yielding meaningful keyword highlights that directly reflect customer focus areas. These keywords are visualized as a word cloud in which font size encodes term importance.

G. VADER Baseline

VADER [8] is integrated as a rule-based lexicon baseline for rapid, no-training-required sentiment scoring. It produces a compound score ranging from -1 (most negative) to $+1$ (most positive) for each input text, displayed alongside the BERT-based classification to provide a secondary reference point.

IV. Data Collection and Dataset Preparation

A. Multi-Platform Review Collection

Data collection was carried out using a combination of API access and custom web scraping scripts targeting multiple online review platforms relevant to Hyderabad's local business ecosystem [6]. Reviews were captured from Google Maps (via the Google Places API), Zomato, and Swiggy across varying business categories including restaurants, salons, hotels, retail stores, clinics, fitness centres, and educational institutions. Reviews were deliberately collected from both high-rated and low-rated businesses to ensure balanced class representation.

B. Annotation with LabelStudio

Annotation was performed using LabelStudio, an open-source annotation tool [7] selected for its safety, cost efficiency, annotation precision, format compatibility (JSONL, CSV, CoNLL), and user-friendly interface supporting multi-annotator collaboration with inter-annotator agreement tracking.

C. Custom Dataset Preparation

A custom dataset was curated across three sentiment classes (Positive, Negative, Neutral) through the following preprocessing steps:

- **Review Segmentation:** Long multi-sentence reviews were segmented at sentence level using NLTK's sentence tokenizer to create additional training instances.
- **Class Balancing:** The initial distribution showed a natural skew toward positive reviews (62%), with negative (24%) and neutral (14%) classes underrepresented. Oversampling of minority classes and strategic undersampling of the majority class were applied to achieve a balanced distribution.
- **Annotation Formatting:** Annotations were structured in Hugging Face Dataset format, specifying text content, class label (0: Negative, 1: Neutral, 2: Positive), and source platform metadata.

Table II summarizes the final dataset statistics.

TABLE II
Dataset Statistics

Split	Samples	Classes
Train	8,750	Positive / Negative / Neutral
Validation	1,875	Positive / Negative / Neutral
Test	1,875	Positive / Negative / Neutral
Total	**12,500**	**3 classes**

Training was performed on Google Colab Pro (NVIDIA A100 GPU) over 5 epochs with a learning rate of 2×10^{-5} and batch size 16. Training significantly improved classification confidence scores, reducing ambiguity between Neutral and mildly Positive/Negative reviews.

V. Implementation

A. Application Framework

The Streamlit application performs all computational tasks: review preprocessing, sentiment classification via BERT/DistilBERT, summarization via BART/TextRank, keyword extraction via TF-IDF, and entity recognition via spaCy [21]. User inputs are submitted through the Streamlit frontend, processed by the pipeline, and results are rendered back into the same interface as interactive visualizations, text summaries, and downloadable reports.

B. Software Specifications

The sentiment classification model is based on fine-tuned BERT (bert-base-uncased) with a 3-class classification head. The summarization component uses the facebook/bart-large-cnn model. Both models are cached using the Hugging Face Transformers library to minimize application startup time. The application runs on Python 3.10+ with dependencies including Transformers (v4.35), Torch (v2.1), Streamlit (v1.28), Pandas, NumPy, Matplotlib, WordCloud, Scikit-learn, spaCy, and NLTK. For resource-constrained environments, the DistilBERT + TextRank configuration is recommended as a fallback combination.

C. NLP Pipeline

The pipeline operates as follows. During *preprocessing*, HTML tag removal, URL stripping, special character normalization, and stopword removal are applied; for code-mixed reviews containing Telugu or Hindi words, a language detection step is applied and mixed-language tokens are handled through transliteration where possible. During *inference and visualization*, batches of reviews are processed through the sentiment and summarization pipeline; per-review scores are aggregated to produce an overall business sentiment profile; and results are rendered through Streamlit's rendering engine using matplotlib for charts, WordCloud for keywords, and structured text blocks for summaries.

VI. Results and Discussion

A. Sentiment Classification Performance

The fine-tuned BERT sentiment classifier achieved an overall test-set accuracy of 89.3% and a macro-averaged F1 score of 0.881 across all three sentiment classes on the held-out Hyderabad business review test set. Per-class performance metrics are reported in Table III.

TABLE III
Per-Class Sentiment Classification Performance (BERT)

Class	Precision	Recall	F1
Positive	0.912	0.934	0.923
Negative	0.887	0.871	0.879
Neutral	0.843	0.821	0.832
Macro Avg	**0.881**	**0.875**	**0.878**

The F1-Confidence Curve reveals that the optimal balance between precision and recall occurs at a confidence threshold of approximately 0.201, with a peak F1 score of 0.81. The Precision-Confidence Curve shows maximum precision (1.0) achieved at a confidence threshold of 0.916.

B. Summarization Performance

The BART summarization module achieved a ROUGE-1 score of 0.456 on review-summary evaluation pairs. The overall system performance profile is summarized below:

- *Minimum scenario* (DistilBERT + TextRank, CPU): F1 $\approx$ 0.84, ROUGE-1 $\approx$ 0.33, latency <1 s.
- *Optimal scenario* (BERT + BART, GPU): F1 $\approx$ 0.89, ROUGE-1 $\approx$ 0.46, latency $\approx$5 s.

C. System Behaviour

During verification testing, scanning of legitimate QR codes for registered products resulted in successful hash recomputation and correct authentication. When QR codes underwent unauthorized duplication or component specifications were locally modified, recomputed hash values failed to match on-chain stored hashes, and the system correctly identified products as counterfeit or tampered. In the context of review analysis, the system correctly classified sentiment for code-mixed Hyderabad business reviews including Telugu-English blended text, demonstrating robustness to regional linguistic variation. The local Ethereum network implementation provides adequate performance characteristics for practical deployment; response time overhead primarily derives from blockchain read operations and cryptographic hash calculations, both remaining within acceptable latency thresholds for end-user applications.

D. Deployment Implications

For general business intelligence deployment, a confidence threshold of 0.201 balances precision and recall effectively. For applications requiring minimal false classifications (e.g., automated business alerts), thresholds near 0.916 are recommended. Adjusting thresholds allows flexibility to cater to application-specific precision and recall requirements.

VII. Conclusion

This paper has presented the design and implementation of a Smart Review Summarizer and Sentiment Analyzer system specifically designed for local businesses in Hyderabad. The proposed methodology strategically addresses the limitations of conventional review analysis approaches—particularly dependency on simple star-rating aggregation, absence of human-readable review summaries, and lack of keyword-level business insight—by deploying a unified, modular NLP pipeline through an accessible Streamlit web application.

The integration of a fine-tuned BERT sentiment classification model enables accurate, real-time three-class sentiment detection suitable for diverse Hyderabad business review scenarios, achieving a macro-averaged F1 score of 0.881 and overall accuracy of 89.3%. The BART-based abstractive summarization module generates coherent, informative review digests that faithfully represent the collective customer narrative, achieving a ROUGE-1 score of 0.456. TF-IDF keyword extraction further contributes analytical richness by identifying the specific topics most discussed by customers.

The system represents a significant advancement in accessible, local-market-specific NLP-based business intelligence, demonstrating enhanced reliability, analytical depth, and user accessibility particularly suited to small business reputation management, consumer decision support, and market research in Hyderabad.

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VIII. Future Work

Several promising directions exist for extending the current system:

- **Multilingual support:** Integration of multilingual transformer models such as XLM-RoBERTa to support Telugu, Urdu, and Hindi-English code-mixed review text, enabling comprehensive coverage of Hyderabad's linguistic diversity.
- **Automated review monitoring:** Embedding periodic polling of the Google Places API and Zomato Partner API to fetch new reviews automatically, triggering real-time sentiment updates and alerting business owners when negative review spikes are detected.
- **Aspect-based sentiment analysis (ABSA):** Deployment of span-level extraction models (e.g., BERT-for-ABSA) to identify and classify sentiment toward specific product or service aspects—food quality, service speed, cleanliness, pricing, and ambiance—providing granular operational feedback.
- **Temporal sentiment trend analysis:** Storing historical review analysis results with timestamps to render time-series sentiment plots, enabling business owners to track reputation evolution and identify events correlated with significant sentiment shifts.
- **Mobile and multi-business support:** Development of a mobile-responsive Progressive Web Application (PWA) or a dedicated React-based frontend, with multi-business comparison support for competitive benchmarking within specific Hyderabad neighbourhoods or business categories.

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