iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: VI Month of publication: June 2025

DOI: https://doi.org/10.22214/ijraset.2025.72311

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com

Vibe Tracking: Customer Review Insight Platform

Abhishek Kulkarni[1], Mayur Khedkar[2], Pranjali Gawade[3], Tanishka Kirloskar[4], Rohini Jadhav[5]
Department of Computer Engineering, Smt. Kashibai Navale college of Engineering, Vadgaon (SPPU- Pune), Pune, India

Abstract: Vibe Tracking is a web-based platform that automates the end-to-end process of extracting actionable insights from customer reviews on e-commerce and marketing sites. By combining a Flask-powered interface with a fine-tuned BERT sentiment classifier, the system ingests raw text—whether via CSV uploads or real-time streams—cleans and tokenizes it, and assigns each comment to one of five sentiment categories, from "Very Negative" to "Very Positive." Beyond overall sentiment scoring, Vibe Tracking applies aspect-based decomposition and to pic modelling to isolate feedback on specific product features (e.g., battery life, design, price), enabling granular analysis of customer concerns and praise. Attention-heatmaps and confidence scores provide interpretability, helping stakeholders understand and trust each prediction. Designed for scalability and ease of use, Vibe Tracking empowers marketing and product teams to monitor brand perception continuously, prioritize feature improvements, and make data-driven decisions that enhance customer satisfaction and competitive advantage.

Index Terms: Sentiment Analysis, Customer Reviews, BERT, Flask, NLP, Product Feedback, Aspect-based Sentiment Analysis, Topic Modelling, Machine Learning, E-commerce, Marketing Analytics, Real-time Data Processing, Multilingual Support, Predictive Analytics, Data Visualization, Customer Satisfaction, Competitive Intelligence, Web Application, Natural Language Processing (NLP), Edge Computing, Interpretability, Data-driven Decision Making.

I. INTRODUCTION

Vibe Tracking is a cutting-edge web-based platform designed to empower businesses with deep insights from customer reviews, transforming raw feedback into valuable, actionable intelligence. As organizations increasingly rely on customer reviews to gauge satisfaction, identify product issues, and enhance marketing strategies, Vibe Tracking automates the

entire process of feedback analysis to save time and maximize accuracy. The platform allows seamless data ingestion from various sources, including CSV file uploads and real-time feeds from major e-commerce platforms like Amazon, Yelp, Google Reviews, and social media channels. Vibe Tracking provides robust preprocessing capabilities, automatically cleaning and tokenizing the text while filtering out irrelevant content such as slang, emojis, or domain-specific terms. With built-in language detection, it ensures that reviews in multiple languages are handled with precision, seamlessly routing data to the appropriate multilingual models for accurate sentiment analysis. At the heart of Vibe Tracking is its state-of-the-art sentiment analysis engine, built on advanced BERT-based models fine-tuned specifically for product review corpora. This sentiment classifier analyses each review, categorizing it into one of five sentiment scores—ranging from "Very Negative" to "Very Positive." To optimize for speed without sacrificing accuracy, the platform also supports lightweight model variants like Distil BERT, which ensures faster inference times. What sets Vibe Tracking apart is its ability to extract deep insights from reviews. Through aspect-based sentiment decomposition, the platform isolates sentiments related to specific product features such as "battery life," "design," "price," and more. It also applies advanced techniques like keyword clustering and topic modelling to detect emerging trends, enabling businesses to proactively address customer concerns and capitalize on positive feedback. The platform's interactive dashboard offers real-time visualizations, including sentiment distributions, trend lines over time, and geographical heatmaps. Users can drill down into the data, filtering by date ranges, sentiment levels, and specific features to get granular insights into their customers' experiences. This comprehensive analysis is complemented by customizable alerts, which notify users of sudden shifts in sentiment or spikes in negative reviews, helping teams stay on top of urgent issues. In summary, Vibe Tracking is more than just a sentiment analysis tool—it's a comprehensive platform that provides businesses with the ability to understand, interpret, and act on customer feedback in a way that drives product improvement, enhances customer satisfaction, and fuels data-driven decision-making. With its combination of advanced machine learning models, real-time analytics, and user-friendly interface, Vibe Tracking equips organizations with the tools they need to stay ahead in an increasingly competitive market.

II. MATHEMATICAL MODEL

1) Problem Definition

Given a dataset $\mathcal{D} = \{(x^{(i)}, y^{(i)})\}_{i=1}^N$, where $x^{(i)}$ is the comment and $y^{(i)} \in \{1, 2, 3, 4, 5\}$ represents the sentiment label, we aim to learn the model parameters θ such that the predicted sentiment $\hat{y}$ approximates the true sentiment y, i.e., $f(x; \theta) = \hat{y} \approx y$.

2) Data Representation

a) Tokenization: The input comment \(x\) is tokenized into a sequence of tokens: \[T = [\mathtt{[CLS]}, t_1, t_2, \dots, t_n, \mathtt{[SEP]}], \quad |T| = L \] where \(L\) is the length of the tokenized sequence.

b) Embedding: Each token \(t_i\) is represented by an embedding vector \(e_{t_i} \in \mathbb{R}^d\). The token embeddings are combined to form the input matrix \(X\):\[X = [e_{\mathtt{[CLS]}}, e_{t_1}, e_{t_2}, \dots, e_{t_n}, e_{\mathtt{[SEP]}}] \in \mathbb{R}^{L \times d}\] where \(d\) is the dimension of the embeddings and \(L\) is the sequence length.

3) Model Architecture

BERT Encoder: The token embeddings \(X\) are passed through the BERT encoder, which produces a sequence of hidden states \(H \in \mathbb{R}^{L \times d}\).

The output corresponding to the \(\mathtt{[CLS]}\) token, \(h_{\mathrm{CLS}} = H_0\), is used as the representation for the entire input sequence.

4) Softmax & Prediction

The logits \(z\) are passed through a softmax function to obtain class probabilities: \[p_j = \frac{e^{z_j}}{\sum_{k=1}^5 e^{z_k}}, \quad \hat{y} = \arg\max_j p_j\] where \(\hat{y}\) is the predicted sentiment class (1 to 5).

III. RELATED WORK

O'Callaghan, F. V., Newman, D. L., Jones, L., & Creed, P. A. (2017).[1] *Use of lecture notes in higher education: A review of institutional and student lecture topics.*

This article reviews the use and impact of lecture notes in higher education from multiple perspectives, including institutions, students and faculty, addressing benefits such as increased access and flexibility for students. as well as potential problems such as reduced attendance and participation. The authors emphasize the importance of considering stakeholder perspectives when integrating lecture recording technology into educational practices.

Methods The review consisted of a synthesis of available literature and used qualitative analysis of various studies. that focuses on recording lectures. This basic study provides a comprehensive overview of the state of lecture recording technology and its impacts. This makes it necessary to understand the role of technology in the educational environment.

Trafagan, T., Kuxera, J.V., & Kishi, K. (2010).[2] Impact of web-based lectures on participation and learning. This study examines how web-based lecture delivery affects student attendance and learning outcomes. It was found that although participation decreased due to network lectures, but there was no significant learning loss. Because students often use recordings for review and reinforcement. This research used a mixed methods method Hall, G., & Ivaldi, A. (2017).[3] Qualitative approaches to understanding the role of lectures in student learning experiences. This qualitative study explored how students perceived the use of lecture recording technology. It addresses issues such as increased understanding of the content. Flexibility in learning and the possibility of over-reliance on recorded media. The authors conducted interviews and focus groups with students to gather insights into their lecture experiences. These findings reveal the subtle ways in which students engage with lecture notes. It provides valuable information for improving lecture recording strategies. Joseph-Richard, P., Jessup, T., Okafor, G., Almpanis, T., & Price, D. (2006) (2018).[4] Big Brother or Leader Best Practices: Can Lectures Really Improve Learning? This article discusses two characteristics of lecture recording technology as a monitoring tool and a tool for improving learning approaches. The authors argue for the potential to improve educational quality through constructive feedback loops and reflective practices. This article uses a literature review and case study to evaluate two perspectives on narratology. Provides a critical perspective on the impact of using lectures for teaching and learning. It challenges educators to carefully consider these impacts.

IV. LITERATURE REVIEW

1) BERT: Bidirectional Encoder Representations from Transformers (2019) Devlin et al. introduced BERT, a pre-trained model that improved sentiment analysis by capturing bidirectional context, setting new standards for model fine-tuning.
2) Multilingual BERT for Cross-lingual Sentiment Analysis (2020) NLP Town developed a multilingual BERT model effective for sentiment analysis across languages, allowing global sentiment analysis without separate models for each language.
3) Fine-tuning BERT for Sentiment Classification (2021) Sun et al. explored fine-tuning methods for BERT, emphasizing learning rate scheduling and domain-specific pre-training to optimize performance and reduce computational costs.

4) Web-based Sentiment Analysis Using Flask and BERT (2022) This study implemented a Flask-based application for deploying BERT for sentiment analysis, addressing challenges like inference speed and resource efficiency.
5) Real-time Sentiment Analysis with BERT (2022) The research demonstrated how BERT can be optimized for real-time sentiment analysis of continuous data streams, leveraging edge computing for efficiency.
6) Explainable Sentiment Analysis with BERT (2023) This work focused on interpreting BERT's attention mechanisms, improving the transparency of sentiment analysis decisions and identifying biases.
7) BERT-based Sentiment Analysis for User Experience (2023) BERT was used to analyse user feedback for product improvement, offering better accuracy than traditional lexicon-based methods in detecting subtle sentiments.

V. OBJECTIVES

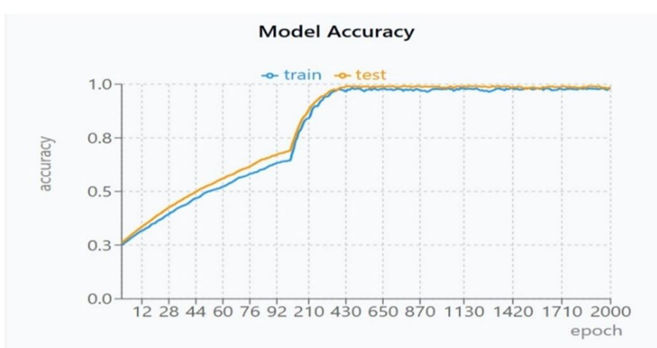
The primary objective is to create a web-based tool that allows users to upload CSV files containing comments and automatically analyse the sentiment of each comment, categorizing them on a 5-point scale from "Very Negative" to "Very Positive.

VI. METHODOLOGY

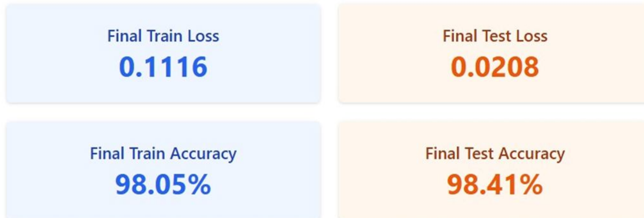
Model Selection: Implements a pre-trained multilingual BERT model for sentiment analysis
Web Application: Creates a Flask-based interface allowing users to upload CSV files
Data Processing: Validates CSV files, extracts comments, and processes them through the model
Sentiment Classification: Analyses each comment and categorizes it on a 5-point scale from "Very Negative" to "Very Positive"
Results Presentation: Displays the original comments alongside their sentiment classifications in the web interface

VII. RESULTS

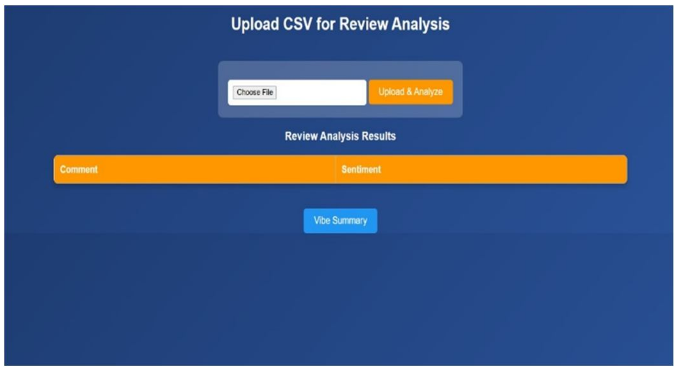
To evaluate the performance of the model, accuracy and loss metrics were monitored over multiple training epochs. Accuracy indicates how correctly the model predicts the outcomes, while loss represents the error in predictions. By plotting both training and testing curves, we can understand how well the model is learning and generalizing to unseen data. A well-trained model typically shows increasing accuracy and decreasing loss over time with minimal gap between training and testing performance**.**

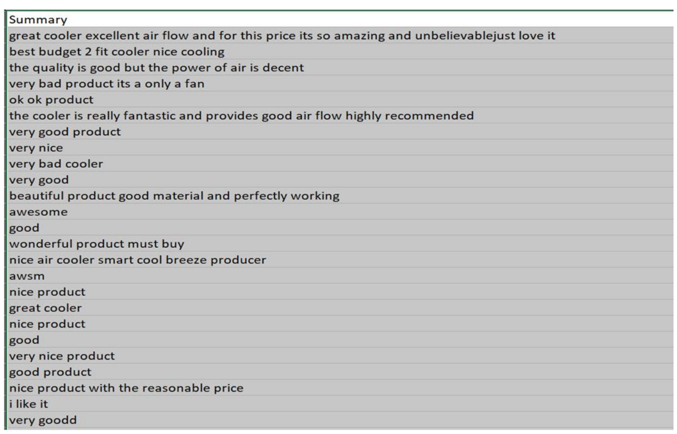


International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com



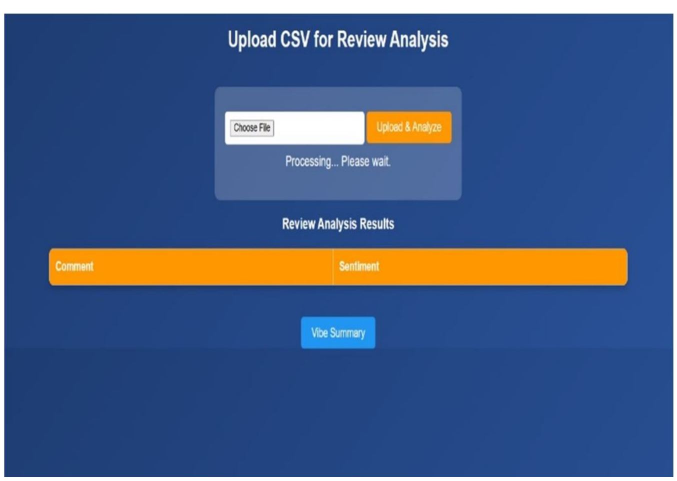
1) Landing Page





Summary
great cooler excellent air flow and for this price its so amazing and unbelievablejust love it
best budget 2 fit cooler nice cooling
the quality is good but the power of air is decent
very bad product its a only a fan
ok ok product
the cooler is really fantastic and provides good air flow highly recommended
very good product
very nice
very bad cooler
very good
beautiful product good material and perfectly working
awesome
good
wonderful product must buy
nice air cooler smart cool breeze producer
awsm
nice product
great cooler
nice product
good
very nice product
good product
nice product with the reasonable price
i like it
very goodd

2) Processing Page



International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com

3) *Actual Analysis*

delivered within 2 days working good	Positive
efficient for large roomspros1 low noise of fan2 inverter friendly3 cools large rooms fastly and easily4 it have aroma chamber in which you can add tablet of frangrance to counter smell of woodwool pads5 it have 2 section for air flow which means you can adjust it to get air for double decker cot equallycons1they should have provided stand of castor wheel for it to move2 it should have ice chamberwill update more about it in future	Positive
better than the steel cooler less noise and value for money	Very Positive
dont buy maharaja whiteline coolers they have cheap aluminum motors that are good for at max 2 years repair cost of these motors is so high that u would want to sell rather than repair them	Very Negative
very nice product and delivery is satisfied	Very Positive
no quality product1 the wood wool has started falling out from the next day2 out of two led indicator has found not working on arrival3 the air swinger is already giving noise when moving which never used to be in my old cooler which i am using since 3 years4 the quality is no way machine to branded coolers5 anti bacterial tank has been bacterial now as there is no way to clean it so congested to maintain it cleanlyin my way think before you buyac has option to aut	Very Negative
air throw is very good it makes room very cool in just half an hour full tank capacity is 65 litres which stays up to 5 hours it makes big living room colder not very much noisy	Positive
on time delivery received exact productthank u flipkart	Very Negative
maharaja always no 1	Very Negative

4) *Review Summery*

Comments Summary

Sentiment Type	Count
Negative	34
Neutral	70
Positive	209
Very Negative	77
Very Positive	312

VIII. KEY ISSUE & CHALLENGES

1) High Computational Requirements -BERT-based models are resource-intensive, requiring substantial memory and processing power, especially during training and fine-tuning phases.
2) Real-Time Inference Latency-Deploying BERT for real-time sentiment analysis introduces latency due to its large model size and complex architecture, affecting user experience.
3) Complex Text Preprocessing-Preprocessing steps such as tokenization, padding, and handling special characters are crucial but add complexity and potential preprocessing errors.
4) Risk of Overfitting-Fine-tuning BERT on small or imbalanced datasets can lead to overfitting, reducing the model’s ability to generalize to unseen data.
5) Limited Interpretability-Transformer models like BERT operate as "black boxes," making it difficult to interpret how decisions are made, which can be a concern in critical applications.

IX. FUTURE WORK

1) Fine-Tuning on Domain-Specific Data-Enhance model performance by fine-tuning BERT on domain-specific product review datasets to improve sentiment classification accuracy.
2) Real-Time Sentiment Tracking-Integrate real-time data pipelines to process live product reviews or social media streams for immediate sentiment monitoring and response.
3) Multilingual Support Expansion-Extend the system to support more languages using additional multilingual models to cater to global users and markets.
4) Explainable AI Integration-Incorporate attention visualization tools to make sentiment predictions interpretable, building user trust and transparency in model decisions.
5) Mobile and Edge Deployment-Optimize and compress the BERT model (e.g., using DistilBERT or quantization) for deployment on mobile and edge devices.

X. CONCLUSION

Vibe Tracking successfully demonstrates how modern transformer-based models can be leveraged to automate and scale the analysis of customer reviews, transforming unstructured feedback into actionable business intelligence. By integrating a fine-tuned BERT sentiment classifier with a user-friendly Flask interface, the platform delivers both overall sentiment scores and aspect-level insights, enabling marketing and product teams to rapidly identify strengths, weaknesses, and emerging trends.

REFERENCES

[1] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv preprint arXiv:1810.04805.
[2] NlpTown (2020). Multilingual BERT for Sentiment Analysis. HuggingFace Model Repository. https://huggingface.co/nlptown/bert-base-multilingual-uncased-sentiment
[3] Sun, C., Qiu, X., & Huang, X. (2019). How to Fine-Tune BERT for Text Classification? arXiv preprint arXiv:1905.05583.
[4] Vaswani, A., et al. (2017). Attention is All You Need. Advances in Neural Information Processing Systems, 30. https://arxiv.org/abs/1706.03762
[5] Wolf, T., et al. (2020). Transformers: State-of-the-Art Natural Language Processing. In Proceedings of the 2020 Conference on EMNLP. https://aclanthology.org/2020.emnlp-demos.6
[6] Flask Documentation (2023). Flask Web Framework. https://flask.palletsprojects.com/
[7] Liu, Y., et al. (2019). RoBERTa: A Robustly Optimized BERT Pretraining Approach. arXiv preprint arXiv:1907.11692
[8] Lan, Z., et al. (2020). ALBERT: A Lite BERT for Self-supervised Learning of Language Representations. In ICLR 2020. https://arxiv.org/abs/1909.11942
[9] Sanh, V., et al. (2019). DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108
[10] Liu, B. (2012). Sentiment Analysis and Opinion Mining. Morgan & Claypool Publishers. https://www.cs.uic.edu/~liub/FBS/SentimentAnalysis-and-OpinionMining.pdf