Kuwait Journal of Advanced Computer Technology
ISSN: 2984-7907
Vol 4 Issue 1 (2026)

Sentiment Analysis of Flipkart Reviews using Distilbert: A Deep Learning Methodology

Dr. Fauja Singh
MGS University, Bikaner, Rajasthan, India
E-mail: faujasingh1983@gmail.com

Submitted: 05/12/2025 **Revised:** 18/12/2025 **Published:** 28/12/2025

Abstract

In the competitive world of e-commerce, customer reviews act as a primary guide for new buyers. When people shop on major platforms like Flipkart, they rely heavily on the experiences of others to decide whether a product is worth their money. For businesses, this feedback is a vital resource; analyzing it correctly can reveal exactly what makes a product succeed or fail. This paper focuses on extracting those insights by applying DistilBERT, an advanced deep learning technique, to Flipkart product reviews. While standard analysis methods often miss the nuance in human language, this approach is designed to capture the true sentiment behind user comments more accurately. By decoding these public opinions with greater precision, companies can fine-tune their marketing strategies and improve their product lineups. Ultimately, this research bridges a gap in the current studies by demonstrating how modern deep learning tools can turn raw review data into a clear roadmap for increasing customer confidence and satisfaction.

Keywords: Sentiment Analysis, Deep Learning, DistilBERT, Flipkart Reviews, E-Commerce Reviews

1. INTRODUCTION

Online customer reviews are essential for understanding consumer preferences and experiences in the market. In the current e-commerce era, these review materials empower consumers to establish purchase intentions and make informed decisions. Consequently, individuals in contemporary society are increasingly reliant on e-commerce platforms or applications for online transactions.

Evaluating sentiment in e-commerce product evaluations is critical for organizations. It allows companies to assess customer sentiment instantaneously, which facilitates enhanced product alternatives and post-purchase assistance. Online buyers depend heavily on evaluations and ratings from prior consumers, which often directly affect a product's success or failure. Similarly, manufacturers and suppliers ascertain the performance of their products by evaluating this customer feedback. By prioritizing customer satisfaction and enhanced experiences, e-commerce platforms have revolutionized consumer shopping.

Social media and online community forums offer companies the opportunity to interact with consumers via direct communication and advertising platforms, enabling them to comprehend consumer viewpoints on products and services. These platforms prompt public discussion about a company's achievements and shortcomings. Consequently, the initial step in cultivating an understanding of customer preferences involves collecting and assessing the online database of customer reviews. Analyzing these reviews allows businesses to generate innovative concepts and understand consumer preferences.

To facilitate the categorization of online feedback, sentiment is typically classified into three categories: positive, negative, and neutral. This study utilizes classifiers to deliver signals to prospective clients regarding specific products. While traditional text classification methods sort feelings into two binary groups—positive and negative —it has become increasingly important to analyze sentiments within data from online sources.

Sentiment analysis uses computational linguistics, text analysis, and natural language processing to extract subjective information, providing insights into human thought patterns, behavior, and societal trends.

2. LITERATURE REVIEW

The literature survey encompasses various authors and their sentiment analysis methods for products and online reviews, aiming to extract features and classify different types of opinions.

Yadav et al. [1] proposed an augmented dictionary approach for sentiment analysis. Although their work does not specifically address Flipkart reviews, it incorporates domain-specific words and achieved an accuracy of 64.56% across diverse domains, including movies, mobile phones, and restaurants. Similarly focusing on specific products, Soni et al. [2] leveraged web scraping techniques to perform aspect-based sentiment analysis specifically for Flipkart mobile phone reviews, effectively deriving insights from user feedback on various product aspects.

Broadening the scope, Adane et al. [3] applied sentiment analysis to product reviews from Flipkart, Amazon, and Twitter. Their study demonstrated the significant influence of social media and public sentiment on consumer behavior and business decision-making. To improve classification accuracy, Nema et al. [4] utilized an ensemble learning model to categorize a diverse range of emotions in Flipkart reviews, addressing the limitations of existing methods that primarily identify negative sentiments.

Several studies have focused on the practical application of these technologies. Amrithkala et al. [5] applied standard machine learning algorithms to automate the analysis of e-commerce feedback, offering a pathway for businesses to identify prevailing consumer trends. Shifting the focus to public health, Singh and Gaur [6] analyzed social media interactions during the COVID-19 pandemic, highlighting sentiment analysis as a crucial early warning system for tracking public emotional landscapes during crises.

Foundational methodologies have also been extensively reviewed. A concise review by [7] summarized key methodologies in the field, reflecting on the transition of sentiment analysis from academic curiosity to an essential industry tool. Meanwhile, Paper [8] focused on using the ARCNN model for product reviews; while not specific to Flipkart, the model improved accuracy through an attention mechanism and BRNN-CNN architecture. Addressing the complexity of language, Paper [9] presented a dual sentiment analysis method to enhance classification in online reviews by addressing polarity shifts and incorporating neutral sentiments.

Research by [10] concentrated on opinion mining, demonstrating how automated systems can harvest subjective details and summarize large datasets of web-based reviews. In a comparative analysis, Paper [11] weighed the advantages of algorithms like Naive Bayes and Decision Trees, providing a guide for balancing processing speed, accuracy, and complexity. Similarly, authors in [12] applied NLP techniques to Amazon data, using logistic regression to decode customer reviews and improve product recommendations.

Understanding the architecture of these systems is vital. Paper [13] explored fundamental architectures for determining sentiment, offering insights into how early systems struggled with sarcasm and context. A comprehensive survey in [14] categorized dominating techniques into machine learning, lexicon-based, and hybrid approaches. Furthermore, Paper [15] examined the end-to-end implementation of these systems, emphasizing the importance of data visualization for non-technical stakeholders.

Recent trends indicate a shift toward advanced models. A broad survey of the e-commerce sector in [16] identified the increasing use of deep learning and real-time analysis. Addressing data noise, Paper [17] introduced tailored preprocessing methods for YouTube comments to handle slang and emojis. Paper [18] merged statistical techniques with sentiment analysis to cross-reference written opinions with numerical ratings, validating the true sentiment behind scores. Additionally, authors in [19] utilized Hidden Markov Models (HMM) to capture sentiment flow in sequences, while Paper [20] proposed a multi-layered analytical model to process text through various levels of abstraction for richer meaning.

This literature survey provides insights into user opinions that can improve marketing strategies, delving into the diverse techniques employed in analyzing product and online reviews.

3. METHODOLOGY

This study adopts a transformer-based deep learning approach for sentiment classification using the DistilBERT model to analyze product reviews from the e-commerce platform Flipkart. The overall workflow of the methodology is illustrated in Fig. 1.

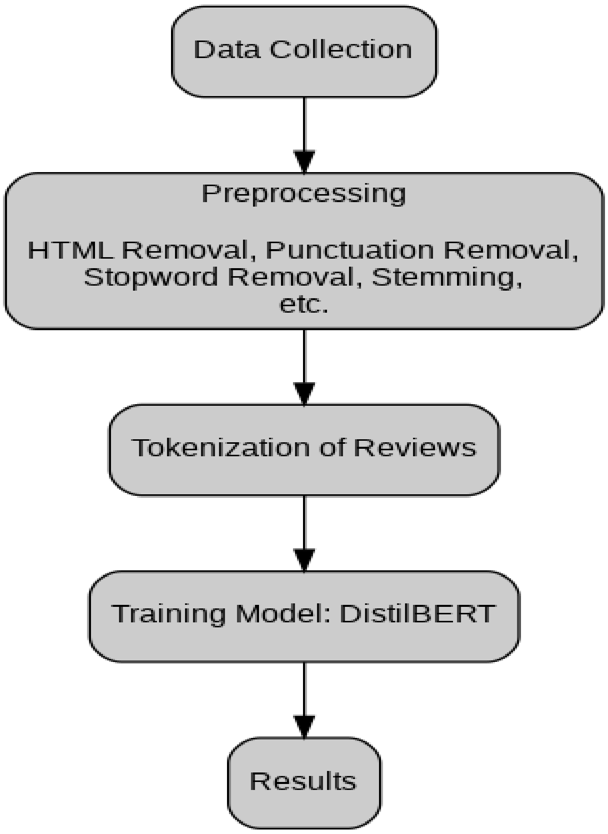

Fig.1. Methodology

3.1 Data Collection:

The study focuses on gathering consumer opinions from product reviews on the prominent e-commerce site, Flipkart. Evaluating these sentiments is crucial for understanding customer preferences and experiences. The dataset used in this study was obtained from Kaggle and comprises 205,252 online customer reviews.

Table:- 1: Sample Dataset

product_name	product_price	Rate	Review	Summary	Sentiment
-	3999	5	mind-blowing purchase	cooler works fine and it is inverter friendly	positive
-	3999	1	waste of money!	small wire and moter capacity is very low fan speed was not good out flow vent hole is above the lower part of	negative

				cooler its very difficult to change water	
-	3999	5	must buy!	perfect product for large size room	positive
-	3999	4	good not best	average cooling not much as expected by size and reviews of cooler cooling is sufficient maharaja whiteline should work on its cooling efficiency and reduce size by width can increase in height to maintain tank capacity	positive
-	3999	5	must buy!	product was amazing cooling capacity awsum pls go for ahead a big thumbs up	positive
-	3999	4	does the job	good	positive
-	3999	3	nice	received dalay 10 days cooler is ok when i was reveived switch damaged	negative
-	3999	3	nice	very nice	positive
-	3999	1	unsatisfactory	very bad cooler	negative
-	3999	4	worth the money	very good	positive

Each record in the dataset consists of textual review information, a summary, a numerical rating, and a sentiment label. A sample of the raw dataset is presented in Table 1. The dataset poses a three-class classification problem, where reviews are categorized as Positive, Negative, or Neutral. The distribution of frequently occurring words in the corpus is visualized in the Word Cloud in Fig. 2.

Fig.2. Word Cloud of Review

3.2 Preprocessing:

Data cleaning and organization are essential for improving sentiment analysis performance. This study applied a robust preprocessing workflow to prepare the textual data, which included:

- HTML Removal: Stripping HTML tags using BeautifulSoup.
- Noise Reduction: Elimination of URLs, punctuation, digits, and special characters using regular expressions.
- Normalization: Converting all text to lowercase.

- Tokenization: Splitting text into individual words.
- Stopword Removal: Removing common English stopwords to reduce irrelevant terms.
- Stemming: Applying the Snowball Stemmer to normalize word forms.

The distribution of ratings across the dataset is depicted in Fig. 3. Since deep learning models require numerical inputs, the categorical sentiment labels were mapped to integer values using the following explicit mapping strategy:

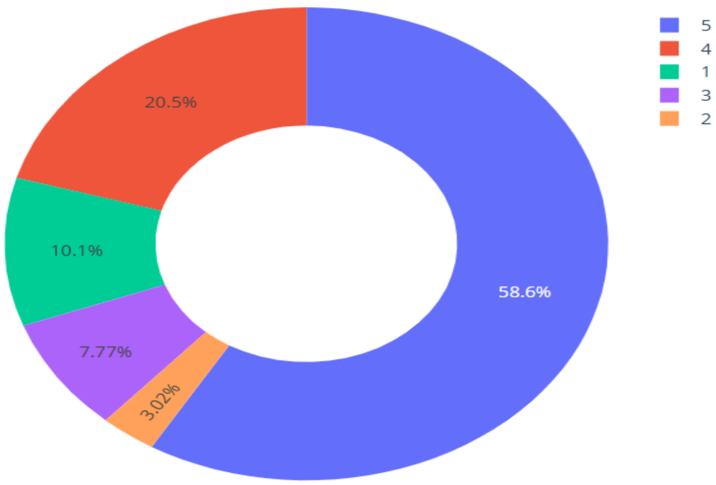

Fig.3. Distribution of ratings

As deep learning models require numerical labels, categorical sentiment classes were mapped to integer values using an explicit label mapping strategy. The mapping scheme adopted in this study is as follows:

- Negative → 0
- Neutral → 1
- Positive → 2

Rows containing invalid or missing sentiment labels were removed to ensure consistency. Finally, to evaluate the generalization capability of the model, the dataset was split into training (80%) and validation (20%) subsets.

3.3 Feature Selection:

To prepare the textual data for the transformer model, the study utilized the distilbert-base-uncased tokenizer. This tool translates raw text into the specific numerical format (input IDs and attention masks) required by the architecture.

The workflow involved converting the cleaned data into Hugging Face Datasets and processing the text in batches. A data collator was implemented for dynamic padding, ensuring that all text sequences were adjusted to a uniform length to maintain computational efficiency. The distribution of review lengths is shown in Fig. 4.

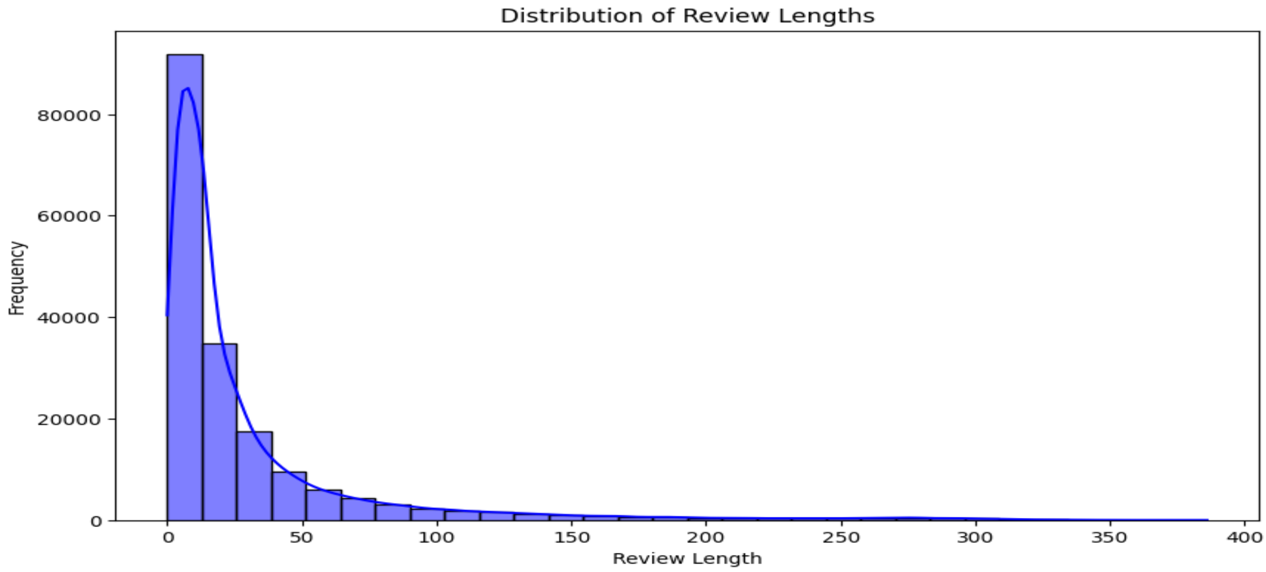

Fig.4. Length of Review

3.4 Model Architecture:

The proposed model is based on DistilBERT, a lightweight and efficient variant of BERT. DistilBERT retains approximately 97% of BERT's language understanding capabilities while significantly reducing computational overhead and memory usage.

The model was fine-tuned for sequence classification using the TensorFlow implementation of Hugging Face Transformers. The training configuration was set as follows:

- Loss Function: Sparse Categorical Cross-Entropy (from logits)
- Optimizer: Adam with weight decay
- Learning Rate: 2×10^{-5}
- Batch Size: 16
- Number of Epochs: Up to 10 with early stopping
- Evaluation Metric: Accuracy

4. RESULT

DistilBERT was chosen for this study because it delivers near state-of-the-art performance with significantly reduced computational overhead, making it an ideal model for sentiment analysis tasks that require both accuracy and efficiency. Its ability to leverage contextual information while remaining lightweight aligns well with the objectives of this research.

Model performance was evaluated on the validation dataset using accuracy as the primary metric. Training and validation accuracy curves were plotted to analyze learning behavior and convergence trends across epochs. The experimental results, detailed in Table 2, demonstrate that the proposed methodology significantly enhances the sentiment analysis of Flipkart product reviews.

Table 2: Training and Validation Metrics

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.9172	0.9218	0.2509	0.2379

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
2	0.9304	0.9236	0.2114	0.2314
3	0.9405	0.9236	0.1812	0.2428
4	0.9490	0.9215	0.1560	0.2731

After the fourth epoch, the pre-trained DistilBERT model achieved a training accuracy of 94.90% and a validation accuracy of 92.15%. Additionally, the model recorded a 15.60% training loss and a 27.31% validation loss. These values consistently demonstrate a high degree of accuracy in the predictions. The convergence trends indicate a well-trained model that effectively balances learning from the training data while generalizing to new validation data. The training and validation accuracy trends are visualized in Fig. 5.

Fig.5. Accuracy of Model

Experiments were conducted on the Google Colab platform with GPU acceleration using Python 3. The system was configured with approximately 12.7 GB of system RAM, a 15 GB GPU, and 112.6 GB of disk storage (as shown in Table 3), which was sufficient for fine-tuning the DistilBERT model.

Table 3: System Specifications

Component	Specification
Runtime	Google Compute Engine
GPU	15 GB
RAM	12.7 GB
Disk	112.6 GB

5. CONCLUSION

This study demonstrates that DistilBERT is capable of achieving near-BERT-level performance in sentiment classification while significantly reducing computational complexity and training time. By examining the attitudes expressed in reviews, this research highlights how businesses can gain a critical understanding of consumer opinions regarding their products and services. The findings reveal that public opinions play a pivotal role in determining the success or failure of products in the marketplace.

Furthermore, the study underscores that consumer involvement through reviews enhances the interaction between businesses and their customers, as individual reviews often shape the behavior and decision-making of prospective buyers. Ultimately, this research provides a deeper understanding of consumer attitudes, offering a valuable tool for businesses to refine their marketing strategies and product offerings. The methodology employed in this paper serves as a robust framework for improving e-commerce business strategies and better grasping consumer sentiment.

REFERENCES

[1] Seema Yadav, N. Saleena. (2020). Sentiment Analysis Of Reviews Using an Augmented Dictionary Approach. International Conference on Computing, Communication and Security (ICCCS). doi: 10.1109/ICCCS49678.2020.9277094

[2] Jitendra Soni, S. Joseph Xavier, R. N. Saxena, Priansh Waghela. (2024). Leveraging Web Scraping for Aspect-Based Sentiment Analysis: A Case Study on Flipkart Customer Reviews of Mobile Phones. International Journal of Research Publication and Reviews. doi: 10.55248/gengpi.5.0624.1638

[3] Padma Adane, Avanti Dhiran, Shruti Kallurwar, Sushmita Mahapatra. (2024). Sentiment Analysis of Product Reviews from Amazon, Flipkart, and Twitter. Springer Nature. doi: 10.1007/978-981-99-9489-2_33

[4] Neetesh Nema, Vivek Shukla, S. R. Tandan, Amit Pimpalkar, Rohit Miri, Vishnukant Soni. (2024). Sentiment Analysis Using an Ensemble Approach on Flipkart Societal Media Data. IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). doi: 10.1109/sceecs61402.2024.10482343

[5] Amrithkala M. Shetty, Mohammed Fadhel Aljunid, D. H. Manjaiah. (2023). Sentiment Exploring on Feedback of E-commerce Data Using Machine Learning Algorithms. Springer Nature. doi: 10.1007/978-981-99-7622-5_8

[6] Fauja Singh, Vishal Gaur. (2024). Sentiment Analysis of data from Social Media Platforms on COVID-19 using Machine Learning Algorithms. Journal of Research and Development. doi: 10.5281/zenodo.16894945

[7] Samiksha Rahate, Vaishnavi Dehanka, Tanvi Teppalwar, Vaishali Surjuse. (2022). Review Sentimental Analysis. International Journal of Computer Science and Mobile Computing. doi: 10.47760/ijcsmc.2022.v11i03.005

[8] Xiaoyu Xu, Ming Xu, Jian Xu, Ning Zheng, Tao Yang. (2017). Sentiments Analysis of Reviews Based on ARCNN Model. IOP Conference Series: Materials Science and Engineering. doi: 10.1088/1757-899X/261/1/012023

[9] Divya Kumari, Himmat Singh, Aditya Mishra. (2016). Sentiment analysis of online user reviews. International Journal of Modern Trends in Engineering and Research.

[10] Kimberley Faria, Karen Carvalho, Arshiya Thakur, Sarika Davare. (2017). Sentiment Analysis of Reviews using Opinion Mining on Web. International Journal of Computer Applications. doi: 10.5120/IJCA2017915426

[11] Bhavna Khedkar, Nutan M. Dhande. (2018). Sentiment Analysis of Customer Product Reviews Classification Techniques: A Review. Journal of Emerging Technologies and Innovative Research.

[12] Fauja Singh, Vishal Gaur. (2024). Sentiment Analysis of Amazon reviews with Natural Language Processing using Machine Learning Algorithms. International Advance Journal of Engineering, Science and Management (IAJESM). doi: 10.5281/zenodo.16894928

[13] B. Anil, Aman Kumar Singh, Aman Aditya Kumar Singh, Surekha Thota. (2018). Sentiment analysis for Product Reviews. International Journal of Advanced Research in Computer Science. doi: 10.26483/IJARCS.V9I0.6185

[14] Akansha Srivastava, Ravindra Gupta. (2020). Sentiment Analysis Techniques: A Review. International Journal of Innovative Science and Research Technology. doi: 10.38124/IJISRT20SEP653

[15] Sayali Pednekar, Komal Patil, Rutweek Sawant, Trupti Shah. (2017). Sentiment analysis on online product reviews. International Education and Research Journal.

[16] Yashashri Gayki, Pratham Chatke, Rani Nandane, Umesh Shinde, Manav Ghugare, Priti Rathod, Minal Pardey. (2023). A Survey on “Sentiment Analysis of E-commerce Website’s Reviews”. International Journal for Research in Applied Science and Engineering Technology. doi: 10.22214/ijraset.2023.56255

[17] Fauja Singh. (2024). A Novel Approach to Sentiment Analysis on Youtube Comments using Natural Language Processing and Machine Learning. Bohal Shodh Manjusha. doi: 10.5281/zenodo.16894973

[18] Zeenia Singla, Sukhchandan Randhawa, Sushma Jain. (2017). Statistical and sentiment analysis of consumer product reviews. International Conference on Computing, Communication and Networking Technologies (ICCCNT). doi: 10.1109/ICCCNT.2017.8203960

[19] Swati Soni, Aakanksha Sharaff. (2015). Sentiment Analysis of Customer Reviews based on Hidden Markov Model. International Conference on Advances in Computing, Communications and Informatics (ICACCI). doi: 10.1145/2743065.2743077

[20] Jagbir Kaur, Meenakshi Bansal. (2016). Multi-layered sentiment analytical model for product review mining. Parallel, Distributed and Grid Computing (PDGC). doi: 10.1109/PDGC.2016.7913231