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SentimentAI: Sentiment Analysis of Product Reviews and Evidence-Based Recommendation System

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A B S T R A C T

This paper presents SentimentAI, a full-stack system for analysing customer reviews and summarizing product sentiment. Users can submit a product URL for best-effort review retrieval or paste review text manually when a retailer blocks access. The backend validates inputs, processes available reviews, and classifies each review as positive, neutral, or negative. The system uses a Multinomial Naive Bayes model trained on sampled reviews from the All Beauty and Amazon Fashion categories of Amazon Reviews'23. Star ratings are mapped to sentiment labels, and product-grouped data splits are used to evaluate the classifier. On a 12,000-review test set, the model achieved 71.07% accuracy and a macro-F1 score of 0.702. The dashboard presents sentiment summaries, review-level results, analysis history, product comparisons, saved products, and rule-based recommendations. The system is functional for supported inputs, but retailer access checks may prevent automatic review retrieval. Its reported classification performance is based on two product categories and should not be assumed to generalize to every retailer or product. Results are intended to help users review available feedback more efficiently, rather than replace independent judgment.

Keywords: Sentiment analysis, product reviews, text classification, Naive Bayes, e-commerce, recommendation system

1. Introduction

Online shopping has made it possible to compare products across many retailers, but product pages may contain hundreds or thousands of customer reviews. Reading all of these reviews individually takes time and makes it difficult to identify recurring feedback. Sentiment analysis can help organize opinionated text into categories and summarize the overall polarity of user feedback.

SentimentAI is a web application designed to analyse product reviews and present a concise overview through a dashboard. Users can submit a supported product URL for best-effort retrieval of publicly visible review text. If a retailer requires sign-in, presents human verification, or otherwise blocks automated retrieval, users can paste review text into the manual analysis form.

The system classifies review text into positive, neutral, and negative categories. It also provides supporting review excerpts and additional product-analysis features. These include analysis history, product comparison, saved products, recommendations based on stored results, and a rule-based assistant.

This paper describes the system architecture, model training process, implementation, and evaluation results. It also discusses the limitations of retailer retrieval and the current model, so that the system's outputs are interpreted appropriately.

2. Literature Survey

Huang, Zavareh, and Mustafa reviewed sentiment-analysis techniques used in e-commerce platforms [1]. Their review identifies machine-learning and deep-learning approaches as common methods for analyzing customer feedback, and highlights fine-grained analysis, aspect identification, and handling implicit opinions as continuing research challenges. This work provides a broad overview of the field in which SentimentAI operates.

Several studies focus directly on product reviews. Juyal examined sentiment classification of Amazon customer comments using natural-language processing and machine-learning methods [6]. Kamalesh and Vijayalakshmi also studied sentiment analysis of Amazon product reviews [9]. Sadik *et al.* evaluated machine-learning algorithms and hybrid feature engineering on Amazon reviews, linking sentiment analysis to product aspects such as quality and usability [2]. These studies show the relevance of review classification to e-commerce, while also illustrating that results depend on the dataset, feature representation, and evaluation method used.

Aspect-based sentiment analysis offers more detail than assigning a single polarity to an entire review. Samadanian and Kaedi applied aspect-level analysis to customer reviews about after-sales service [3]. Li *et al.* proposed DualGCN, which combines syntactic and semantic information to identify sentiment associated with specific aspects [5]. Gokul Ram *et al.* investigated deep learning, data augmentation, and explainability for customer-review sentiment analysis [4]. These approaches demonstrate ways to obtain more detailed or interpretable results than basic positive and negative classification.

Other research examines how review-analysis results can support consumers and businesses. Ghose and Ipeirotis studied the relationship between review text characteristics, reviewer characteristics, and review helpfulness [8]. Li and Li used sentiment information from online reviews to analyze product attributes and inform product improvement [10]. Uma *et al.* compared support-vector-machine and convolutional-neural-network approaches for customer-review classification [7]. Together, these studies connect sentiment analysis to review usefulness, product decisions, and the comparison of classification methods.

SentimentAI builds on these areas by combining product-review classification with a web dashboard for presenting analysis results. Its current model uses Multinomial Naive Bayes with word and bigram features, trained on sampled reviews from two Amazon Reviews'23 categories. Unlike the more advanced aspect and deep-learning methods described above, this implementation is a three-class baseline model. Its measured test accuracy is 71.07%, with a macro-F1 score of 0.702, so its predictions should be treated as estimates.

The system also attempts best-effort retrieval from recognized retailer URLs and provides manual review entry when a page cannot be accessed. This retrieval capability is subject to retailer access restrictions, including sign-in and human-verification checks. Accordingly, SentimentAI combines review analysis and dashboard functionality, but does not claim guaranteed review retrieval or performance equivalent to the more specialized methods in the literature

3. System Architecture

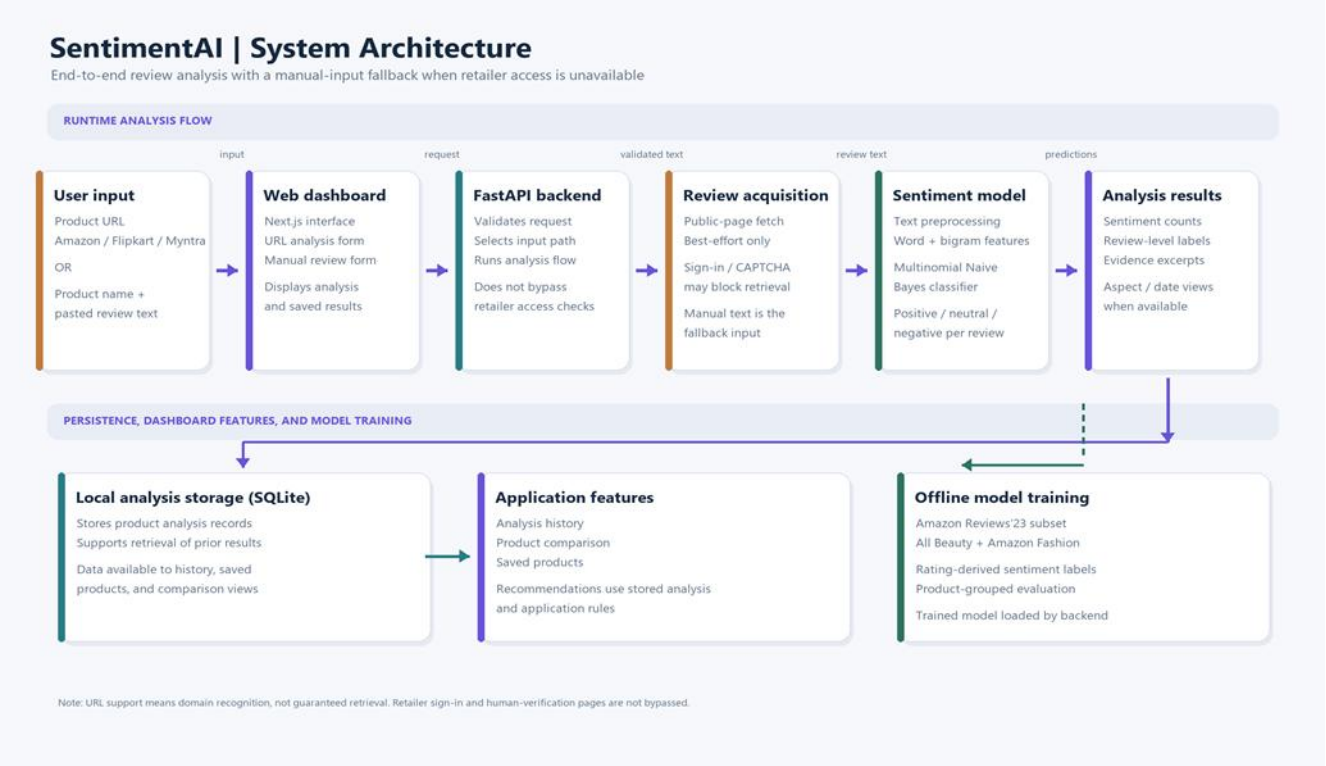


Fig. 1. SentimentAI system architecture showing the frontend, backend, analysis model, and local data storage.

SentimentAI follows a full-stack architecture with separate frontend and backend responsibilities.

3.1 Frontend layer

The frontend provides the user interface for entering product URLs or review text and viewing the resulting analysis. It contains dashboard views for overview, product analysis, history, comparison, recommendations, saved products, and assistant functions.

3.2 Backend layer

The backend is implemented with FastAPI. It validates inputs, processes review text, invokes the sentiment model, and supports application features that use stored analysis data. Product URL retrieval is best-effort and depends on whether the retailer page exposes review information without authentication or access checks.

3.3 Sentiment model layer

The model applies a Multinomial Naive Bayes classifier to word and bigram features. It returns one of three sentiment labels for each analysed review: positive, neutral, or negative.

3.4 Data and persistence layer

The application stores analysis information locally for features such as history, saved products, and comparison. Recommendations are based on stored analysis results and application rules, rather than a trained personalized recommendation model.

4. Implementation

4.1 URL validation and retailer handling

The URL validation helper accepts absolute HTTP and HTTPS URLs and rejects malformed URLs and URLs containing credentials. Platform detection recognizes Amazon domains, including amazon.in and amazon.com, Flipkart domains, and Myntra domains, including subdomains.

Domain recognition does not guarantee that reviews can be retrieved. Retailer pages can require sign-in, present human-verification checks, restrict automated requests, or change their page structure. When a page cannot be accessed, the application reports the retrieval limitation and provides manual review entry as an alternative. It does not bypass retailer access controls.

4.2 Review processing and classification

Available review text is passed through a text-processing pipeline and converted into word and bigram features. The Multinomial Naive Bayes classifier estimates the probability of each sentiment class and returns the most likely class.

The training data uses rating-derived labels:

- One- or two-star reviews are labelled negative.
- Three-star reviews are labelled neutral.
- Four- or five-star reviews are labelled positive.

Star ratings are a practical source of weak labels, but they do not always correspond exactly to the sentiment expressed in the review text.

4.3 Dashboard and application functions

The analysis dashboard presents the sentiment distribution and review-level classifications. Where information is available, it also displays evidence excerpts, aspect-related summaries, and review-date trends.

The application provides analysis history, saved products, product comparison, and recommendations based on previously stored analyses. Its assistant uses rule-based responses. These features organize the results available in the application and should not be interpreted as independent verification of product quality.

5. Results

5.1 Model evaluation

The classifier was evaluated on a 12,000-review test set with 4,000 examples in each sentiment class. It achieved **71.07% accuracy** and a **macro-F1 score of 0.702**.

Table 1. Confusion matrix for the three-class sentiment model

Actual class	Predicted negative	Predicted neutral	Predicted positive

Actual class	Predicted negative	Predicted neutral	Predicted positive
Negative	3,091	644	265
Neutral	1,222	1,975	803
Positive	154	383	3,463

The results show stronger classification of positive and negative reviews than neutral reviews. Some neutral reviews were classified as either negative or positive, which reflects the ambiguity of mixed or descriptive language and the limitations of rating-derived labels.

5.2 Dataset and evaluation split

The model was trained on sampled reviews from the All Beauty and Amazon Fashion categories of Amazon Reviews'23 [3]. The sample used 60,000 training reviews, 12,000 validation reviews, and 12,000 test reviews. Each set was balanced across the three sentiment classes.

Reviews were grouped by product when creating the splits so that reviews associated with the same product were not spread across training and test data. The classifier used Multinomial Naive Bayes with word and bigram features and a smoothing value of $\alpha = 0.5$.

5.3 Functional behaviour

The system supports manual review analysis and can attempt to retrieve review text from recognized retailer URLs. The dashboard can display sentiment summaries and organize prior analysis results through history, comparison, saved products, and recommendations.

Automatic retrieval depends on retailer access. If a page presents sign-in or human verification, the system cannot retrieve reviews from that page. In such cases, users can analyze review text they have permission to use by entering it manually.

6. Applications

SentimentAI can help users review available customer feedback more efficiently by displaying a summary of positive, neutral, and negative opinions. It can help identify recurring praise or complaints in a supplied set of reviews and provide a basis for comparing analyzed products. The project can also serve as an educational example of integrating a machine-learning text classifier with a full-stack web application. Its history and saved-product features allow users to revisit analyses, while the comparison and recommendation pages organize results already available in the application. The system is intended to assist review exploration. It does not independently establish whether a product is genuine, verify the identity of reviewers, or guarantee that retrieved reviews represent all customers

7. Conclusion and Future Work

This paper presented SentimentAI, a full-stack application for analyzing product review sentiment. It supports best-effort review retrieval from recognized retailer domains and manual review submission when automated retrieval is unavailable. A Multinomial Naive Bayes model classifies reviews as positive, neutral, or negative, and the dashboard organizes results through sentiment summaries and supporting application features. On the 12,000-review test set, the model achieved 71.07% accuracy and a macro-F1 score of 0.702. These results provide a measurable baseline for the current model, but they do not establish equal performance across retailers, product categories, languages, or live review data. Retailer access checks can also limit URL-based retrieval. Future work includes expanding the dataset to additional product categories and languages, evaluating with manually verified sentiment labels, comparing additional classification models, and testing generalization on independent retailer review data. Further evaluation should also measure retrieval success across supported pages and the quality of aspect summaries and recommendations.

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