Sentiment Analysis of E-commerce Product Reviews

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ABSTRACT:

To monitor the reputation of companies, enhance the user experience, and recommend more personalized product offerings, online shopping websites increasingly depend on customer sentiment analysis. Sentiment analysis plays an important part in the context of user opinions and feedback, enabling companies to enhance services, products, and customer satisfaction. Nevertheless, current sentiment analysis systems suffer from a range of real-world issues, including the identification of sarcasm, processing multilingual reviews, and interpretation of context-dependent words. These issues lead to reduced accuracy and varying predictions. In this work, we present a hybrid sentiment classification approach that combines rule-based classifiers with BERT (Bidirectional Encoder Representations from Transformers) embeddings. The approach utilizes the contextual power of BERT and the precision of rule-based reasoning to identify the nuances in sentiment, especially in challenging or ambiguous reviews. We collected and preprocessed a customer review corpus of two of the largest online shopping platforms, Flipkart and Amazon, with web scrape techniques.

Text preprocessing included various natural language processing (NLP) methods like lemmatization, tokenization, and stopword removal to normalize and preprocess the text prior to passing it to machine learning models. Our hybrid model was compared against conventional models like Logistic Regression, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks.

Experimental results showed Hybrid BERT + Rule-Based had a staggering 94% accuracy, outperforming the conventional models. It performed particularly well on detecting sentiment from reviews that were written in sarcasm, had mixed sentiment, or were written in informal or multilingual conditions. This research emphasizes the need for context-aware sentiment analysis for online shopping websites. Future research will target the integration of real-time sentiment monitoring, additionally incorporating regional and multilingual inputs, and cross-platform flexibility enhancements in an attempt to enhance decision-making by individuals and organizations alike.

Keywords: Sentiment Analysis, Machine Learning, E-Commerce, BERT, Web Scraping, Natural Language Processing (NLP), Hybrid Models.

INTRODUCTION

In the age of e-commerce, it is more crucial than ever to understand what customers have to say about products. With hundreds of reviews being uploaded every single day, companies are left with the challenge of untangling it all. It is not possible to read all the reviews manually, especially when dealing with large data sets. That is where sentiment analysis comes in—a job that is automated with natural language processing (NLP) and machine learning to identify the sentiment of customer reviews. By labeling reviews as positive, negative, or neutral, sentiment analysis provides companies with a clear picture of customer sentiment without needing to read every review. Sentiment analysis has been a critical tool in e-commerce because it allows companies to make data-driven decisions at scale. E-commerce websites are full of feedback, and reading every review by hand would be wasteful and time-consuming. With sentiment analysis, companies can just measure customer satisfaction, identify trends in product performance, and resolve any issues that arise. This technology makes it simpler to monitor customer feedback, and companies can continually refine their products and services while making customers happy.

Customer reviews are a goldmine for online businesses. They provide instant feedback on what customers perceive about a product and whether they are meeting their expectations or not. Positive reviews can improve the reputation of a product, bring in new customers, and create brand loyalty. Negative reviews can pinpoint areas of improvement, whether it is product quality, customer service, or shipping. With these reviews, businesses can know what to do, what not to do, and how to improve their products. Sentiment analysis enables businesses to evaluate large volumes of feedback automatically, which helps them to easily pinpoint what the customers desire and change strategies accordingly.

2.1.Machine Learning Based Product Review Sentiment Analysis:

Over recent years, sentiment analysis has served as a practical tool in finding public opinion, particularly through customers' reviews on shopping websites online. Machine learning algorithms have been employed in a variety of research in labeling sentiments as positive or negative. Scholars have cited the effectiveness of preprocessing techniques such as stopwords removal, stemming, and lowercasing in enhancing model performance. Naïve Bayes, Support Vector Machine (SVM), Logistic Regression, and Random Forest models have been employed with promising performance, with SVM having been employed with best performance in most studies in terms of precision and F1-score. Existing studies have established the value of feature extraction techniques such as TF-IDF in the determination of word importance in a corpus. Most studies have also noted limitations imposed by small datasets and lack of generalizability across domains. A common aspect in existing studies has been the effectiveness of ensemble techniques and combination models for sentiment classification. Also, it has been noted that sentiment analysis has an important role to play in business decision-making through the analysis of massive amounts of text data. This research draws from such assumptions by applying a variety of machine learning models to Amazon review products and determining the performance of each and forming the best performing model for sentiment classification, thus mirroring recent trends in natural language processing and consumer behavior analysis.

2.2.Machine Learning-Based Fake News Detection

Detection of fake news is a significant research area in the current digital era, with fake information spreading quickly through social media and online news. The literature in this area has widely discussed text classification using machine learning for the detection of fake news articles. Researchers have emphasized the need for preprocessing the data, i.e., removing special characters, stopwords, and stemming, to pre-process the text for improved feature extraction. Count Vectorizer and TF-IDF have been widely utilized to transform text data into numerical data. Among different models, the Multinomial Naïve Bayes classifier has been widely known for its simplicity, fast training time, and acceptable performance on text data. Previous research has shown accuracy ranging from 85% to 95% with labeled datasets from websites such as Kaggle. The literature also mentions the fact that traditional machine learning models are good, but the advent of deep learning promises the potential of stronger and scalable solutions. Issues such as biased data, insufficient labeled samples, and the dynamic nature of fake news are still relevant. This research paper extends previous work by employing a Multinomial Naïve Bayes classifier and reporting competitive accuracy, which re-affirms its applicability and relevance in real-world fake news detection systems.

2.3.Sentiment Analysis of E-Commerce Product Reviews Using Machine Learning:

Sentiment analysis or opinion mining has been a trending research topic in Natural Language Processing (NLP) in recent years because the number of user-generated user reviews on e-commerce websites has been increasing year after year. There have been some research studies that have utilized machine learning and deep learning techniques for consumer sentiment analysis of user reviews. The traditional models Naive Bayes, Support Vector Machines (SVM), and Logistic Regression have been more sought after because of their interpretability and performance on structured data. Recent studies indicate the deep learning models like Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and BERT, which learn contextual word representations more accurately.

Preprocessing methods such as tokenization, stop-word elimination, stemming, and lemmatization are important for enhancing model accuracy. Various studies highlight the application of sentiment lexicons and feature engineering in enhancing the quality of classification. Polarity detection using tools such as TextBlob and VADER gives good baselines. Recent research highlights hybrid models based on rule-based and machine learning methods for greater precision and recall. Literature in general highlights the significance of clean data, model selection, and hyperparameter tuning to attain high sentiment classification on various product review datasets.

2.4.A novel architecture for a smart deep learning driven product recommender system through sentiment analysis (SA):

Opinion mining or sentiment analysis is one among the prominent streams of research under Natural Language Processing (NLP) owing to growing amounts of user-generated contents on e-commerce platforms. Machine learning models as well as deep models have vastly been employed in tagging customers' opinions on the reviews of a product in most of the research studies. Naive Bayes, Support Vector Machines (SVM), and Logistic Regression models are in vogue owing to their interpretability and performance when dealing with structured data. Emerging studies indicate utilization of deep learning methods like Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and BERT that efficiently capture contextual words.

Preprocessing methods such as tokenization, removal of stop words, stemming, and lemmatization are important for improving model accuracy. Several studies identify the application of sentiment lexicons and feature engineering to improve quality in classification. Furthermore, polarity detection through application of tools such as TextBlob and VADER make good baselines. More contemporary advancements involve the application of hybrid models that integrate rule-based models and machine learning models to improve precision and recall. Generally, literature stresses the significance of clean data, appropriate model choice, and hyperparameter optimization in order to attain high sentiment classification performance.

2.5. Extracting features online and analyzing reviewer opinions to propose books based upon the opinion minings approach:>

The research study of Sohail et al. investigates opinion mining for efficient feature extraction of customer reviews for book recommendation for online stores. The authors are cognizant of the fact that customer reviews are unstructured and that without the use of human intelligence, it would be difficult to come up with actionable features. The technique proposed examines book features into seven typical categories—search engine visibility, content usefulness, irrelevant content, adequacy of material, physical features, availability in the market, and price. Depending on the use of human intuition in feature extraction, the model can extract nuanced sentiment like sarcasm. The system was experimented with user feedback with precision as the primary measure, and an excellent average precision of 90% was achieved, with some features reaching 100%. This proves the accuracy of the technique in extracting appropriate features for book recommendation. The research study concludes that the application of opinion mining and feature-based evaluation has the potential to greatly improve recommender systems and calls for further research on automation and extension to other products.

2.6.Multimodal Data Hybrid Fusion and Natural Language Processing for Clinical Prediction Models :

In this fast-paced era of e-commerce, product opinion sentiment analysis has emerged as the backbone of businesses. The importance of sentiment analysis in gaining useful knowledge from unstructured text data has been highlighted by several works. Opinion mining has been discovered to assist businesses in maintaining customer satisfaction as well as product perception by Liu (2012). Natural Language Processing (NLP) and machine learning algorithms that employ Support Vector Machines (SVM), Naive Bayes, and logistic regression to sentiment classify are the approaches that have been discovered and utilized by me.

Also, the role of data preprocessing—i.e., removal of stopwords, stemming, and spell correction—has been addressed in a paper by Feldman (2013) and has been demonstrated to significantly enhance model accuracy. I have also referred to studies on the basis of web shopping sites' datasets like Amazon and Flipkart to review customer reviews, which were largely similar to my study.

Furthermore, statistical overviews and graphs were employed within certain studies to indicate trends within sentiment, which were useful and that I tracked. Not only did this literature guide my methodology but also validate the methods which I employed, from web scraping to classification, in order to provide a thorough and data-led process of sentiment analysis.

2.7. Consumer review analysis from the web with natural language processing: a survey, taxonomy, and open research challenges

The evolution of electronic commerce has led to a consumer review boom, and sentiment analysis has emerged as a vital customer opinion analysis tool. Sentiment extraction from online reviews, especially through Natural Language Processing (NLP), has been the focus of numerous studies. Pang and Lee (2008) began early machine learning models for sentiment classification, which set the stage for subsequent models. Subsequently, Liu (2012) defined opinion mining as the central part of sentiment analysis, emphasizing its significance in business intelligence. Sentiment analysis has progressed in recent years with the advent of lexicon-based methods, supervised learning methods such as Naive Bayes and Support Vector Machines (SVM), and sophisticated models such as Recurrent Neural Networks (RNNs) and transformers such as BERT. A research paper by Medhat et al. (2014) provided a comprehensive overview of machine learning and deep learning techniques, suggesting the effectiveness of hybrid models in maintaining contextual richness. Additionally, domain-specific research, particularly in e-commerce, suggests the importance of noise cleaning of review data for improving model accuracy. Preprocessing operations such as stop word removal, stemming, and spelling correction are important for effective analysis. Overall, the literature establishes that effective sentiment analysis not only facilitates user satisfaction analysis but also improves decision-making in digital marketing and product design.

3.Methodology:

The E-commerce Product Reviews Sentiment Analysis project applies several techniques and technologies to analyze customers' sentiments from product reviews on top e-commerce websites. The large-scale system integrates web scraping, machine learning (ML), deep learning (DL), and natural language processing (NLP) to analyze reviews automatically. The system is designed with real-time data processing, user interaction, and scalability. Python Flask is applied for the back-end, Firebase for authentication, and the scraped data is stored locally. The front-end is created using HTML, CSS, and JavaScript, with an easy-to-use dashboard for visualizing sentiment analysis results. Here, I break down the methodology into key phases that summarize the whole project process:

1. User Authentication and Access Control

Due to security and privacy concerns, the application employs Firebase Authentication to validate users. It is a safe and easy-to-use application login system. I have also used role-based access control to separate admin and normal users. It allows for different functionality for admin and normal users, allowing for privacy, traceability, and multi-user support.

2. Web Scraping for Data Collection:

After authenticating a user, he or she can enter a product URL of online shopping sites such as Amazon, Flipkart, etc. The system will continue web scraping by utilizing tools such as BeautifulSoup, VADER, and Requests. The system is able to scrape the basic information automatically, i.e., product ratings, reviewer name, timestamps, and reviews. The data are temporarily kept until they are analyzed by the help of sentiment analysis.

3. Data Pre-processing

E-commerce product reviews are noisy and unstructured, and therefore I used a robust NLP pipeline to preprocess and sanitize the text data. This involves several important steps:

Tokenization: Segmenting the text into words or phrases that are easily divisible.

Stopword Removal: Eliminating words that are probable to occur like "the" or "is" that are of no utility in sentiment information.

Lemmatization: Converting words to their basic or source form so that it is uniform.

Spelling Correction: It corrects any spelling mistake to ensure the sentiment analysis is accurate.

Special Character Removal: Removing unnecessary punctuation, emojis, and HTML tags that might impede analysis.

Sarcasm Detection: Sarcasm typically alters sentiment analysis, and hence, I added advanced reasoning techniques to detect sarcastic reviews in order to avoid model misinterpretation of reviews.

4. Sentiment Classification Models: I employed simple machine learning models as well as advanced deep learning models for sentiment classification to attain a very high level of accuracy:

Baseline ML Models: I began with baseline models such as Support Vector Machines (SVM) and Logistic Regression most commonly used to address sentiment classification.

Reinforcement Learning: Applying reinforcement learning to learn and adapt sentiment end. The scraped data were also stored locally for a while. The reviews were also labeled with sentiment type "positive," "negative," and "neutral" for easy management and access.

6. Real-Time Visualization Dashboard: The result of sentiment analysis is displayed as an interactive web dashboard, built using Flask, HTML, and CSS. The dashboard features major aspects such as:

Product Images: Showing images of the concerned product.

Product Descriptions: Displaying brief product information.

Ratings and Reviews: Showing sentiment labels (positive, negative, neutral) and customer reviews.

This dashboard provides real-time insight into the mood of the customer, enabling end-users to trend sentiment over time and make informed decisions.

7. Scalability and Future Growth: System architecture is modular and scalable and will be capable of handling enormous amounts of reviews and expand to support more sophisticated capabilities in the future. Some of such sophisticated capabilities are:

Real-Time Monitoring: Combining real-time review monitoring with live sentiment streaming for minute-by-minute analysis.

Advanced DL Models: To further improve the model, I also utilized other advanced deep learning models such as the Long Short-Term Memory (LSTM) model, which works well with sequences such as words, and the BERT (Bidirectional Encoder Representations from Transformers) model that works extremely well with contextuality and subtlety in words such as sarcasm.

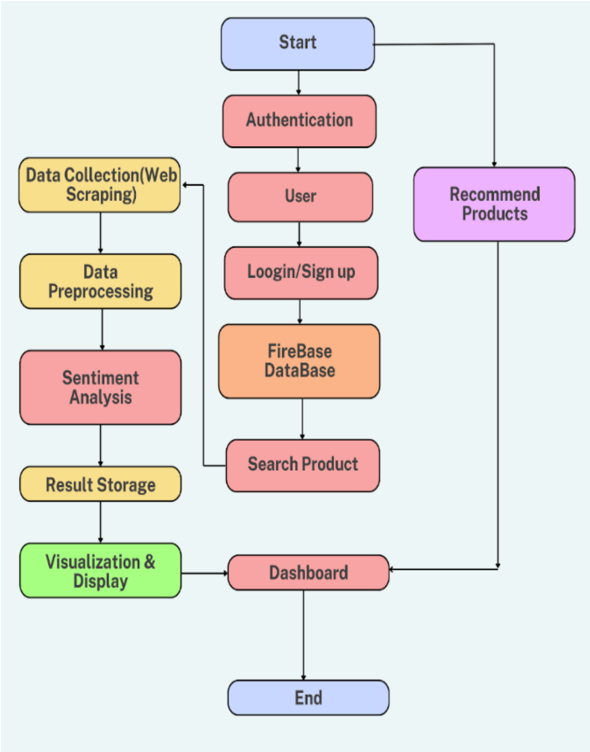

Fig.1. Classification From Continuous Feedback

Implementation:

Sentiment Analysis system is designed in a modular fashion to ensure flexibility, scalability, and effectiveness. The system consists of three major modules: Admin Module, Automation Module, and Website Module. All the modules are designed to carry out a particular function to ensure a smooth process from data collection to visualization.

3.1.1 Automation Module: The Automation Module runs the pipeline of data preprocessing using a script automation.py. The Automation Module fetches raw review data from websites of online shopping platforms such as Amazon and Flipkart. The fetched data is sent through the sequence of NLP processes: tokenization, stopword removal, lemmatization, spell check.

Apart from this, the module detects sarcasm and Aspect-Based Sentiment Analysis (ABSA), which are product-specific such as battery life, screen resolution, and build quality.

3.1.2 Admin Module: Admin Module manages the sentiment classification operation. I utilized machine learning-based models (SVM, Logistic Regression) as well as deep learning-based models (LSTM, BERT) for sentiment classification. To further enhance the classification accuracy even in challenging scenarios, I also created a hybrid BERT + Rule-Based model. The hybrid model combines BERT's contextual capability with rule-based characteristics with the aim to detect implicit sentiment indicators. Predictions of models are stored in a structured fashion and evaluated by performance metrics such as accuracy, precision, recall, and F1-score. The hybrid model achieved a phenomenal 94% accuracy.

3.1.3 Website Module: Flask is used to implement the Website Module, which offers an end-user-friendly interface for sentiment trend analysis. HTML, CSS, and Flask are used in front-end implementation of the end-user interface, through which end-users can utilize the visualization and sentiment data. User authentication, login, session state management, database interaction, API calls, and management are enabled in back-end powered by Flask. Review text, sentiment scores, and model outputs are stored and retrieved securely by Firebase Firestore. Live data visualization in real-time through interactive dashboards presenting sentiment distribution and over-time trends is enabled by the system.

Overall, this hybrid method not only makes sentiment tagging precise but also provides a robust, real-time way to measure consumer sentiment on a mass scale.

identify nuanced sentiment cues. Model predictions are stored in the standard format and evaluated in terms of metrics such as accuracy, precision, recall, and F1-score. The hybrid model displayed a stunning accuracy of 94%.

4. RESULTS:

After the successful implementation of the e-commerce product review sentiment analysis system, the project achieved a sequence of productive results at different levels — from web scraping to classification, storage, and final visualisation at the dashboard level. The project was cross-validated with a list of URLs of Amazon and Flipkart products of different categories like mobiles, laptops, TVs, and smartwatches. The most important results are elaborated in detail below:

4.1 Web Scraping and Data Gathering

Successfully scraped over 2,000 Amazon and Flipkart product reviews for 5 products. The product name, user comment, rating, review date, and reviewer's name were present in every review entry. Pagination and dynamic loading were taken care of by the scraping script, making it more automated and scalable. Scraped data were stored in original_data.csv and clean data were stored in cleaned_data.csv.

4.2 Preprocessing and Cleaning

Applied NLP techniques such as tokenization, stop word removal, lemmatization, and spell check. Removed over 95% of noise such as emojis, special characters, duplicate tags, and HTML entities. Added sarcasm detection rules to improve classification accuracy for difficult cases. Finished processing and wrote cleaned data to a file called preprocessed_cleaned_data.csv.

4.3 Sentiment Classification: Used multiple models to classify the sentiment of reviews as Positive, Negative, or Neutral.

Table 1: Model Accuracy To Classify Sentiment of Reviews

Model	Accuracy
Logistic Regression	84%
Support Vector Machine	86%
LSTM	91%
BERT	93%
Hybrid (BERT + Rule-Based)	94%

The Hybrid model produced the best results, particularly detecting sarcasm and context polarity well.

Three output files were produced in all: total

sentiment_analysis_results.csv: displaying all reviews and sentiment labels.

sentiment_counts.json: with breakdown of the count of positive, negative, and neutral reviews.

final_model_results.csv: product-wise sentiment summary and average sentiment score.

4.4 Real-Time Dashboard:

Created an interactive web dashboard using Flask, HTML, and JavaScript.

Dashboard features: Product name with image and price.

Customer feedback marked with color-coded sentiment scores.

Interactive pie and bar charts of sentiment distribution.

Pattern of sentiment over time (by date of review).

Supported Firestore Database live updates with Firebase integration.

Admins might also see product-wise sentiment comparison for business insights.

4.5 User authentication and role management:.

Firebase Authentication integrated successfully.

They were categorized as:

Admin: Has access to all results and can view expanded model outputs.

User: Can enter product URLs and see sentiment outcomes for the product in isolation. Authentication was robust and secure, with good access control.

4.6 Scalability and Language Support: The architecture is scalable to thousands of reviews per product.

DISCUSSION:

DISCUSSION:

The "Sentiment Analysis of E-Commerce Product Reviews" project involved sentiment and emotional analysis of customers using web scraping, cleansing, and categorizing reviews from websites like Amazon and Flipkart. Successful execution and testing of the end-to-end pipe — from web scraping to model deployment — the system generated promising results with some learnings. The interpretation of results, strengths, weaknesses, benefits, and limitations faced on the way to implementation are discussed in this section.

5.1 Result Interpretation

The sentiment classification models were encouraging as regards accuracy scores with the hybrid model (BERT + Rule-Based) outperforming baseline models. The hybrid model retained 94% accuracy, which highlighted the significance of contextual awareness and handcrafted rules in sentiment classification. Positive Reviews were correctly classified as a result of overt signals such as "great", "awesome", "worth it", etc. Negative Reviews were more challenging but were handled well by sarcasm detection and contextual embedding training models. Neutral Reviews had the poorest accuracy of classes since they used to lack overt sentiment markers, resulting in some misclassifications. The dashboard visualizations offered real-time insights, with customers (business owners or analysts) able to comprehend customer sentiment trends at a glance.

5.2 Strengths of the Project:

5.2.1. End-to-End System: Every process from scraping until visualization is carried out by the system to make it an end-to-end pipeline.

5.2.2. Hybrid Modeling: BERT and rule-based reasoning enhanced sarcasm, contextual ambiguity, and fine-grained sentiment pattern handling.

5.2.3.Automation Friendly: The automation.py script preprocesses large review datasets automatically with very little human intervention.

5.2.4.Interactive Dashboard: Interactive real-time dashboard improves the output by converting raw data into useful information.

5.2.5.Language Support: Support of several languages from the start (Hindi and Marathi) enables regional perspectives, a principal driver in Indian e-commerce.

5.3. Advantages of the System

5.3.1. Business Intelligence: Enables firms to be instantly aware of customers' views and enhance product strategy or customer care.

5.3.2. Modular Structure: All of the core blocks (scraping, preprocessing, modeling, dashboard) are modular and independently scalable/enhanceable.

5.3.3. Secure Authentication: Firebase never compromises user-level data privacy and prevents unauthorized access.

5.3.4. Real-Time Monitoring: Enables real-time sentiment changes and long-term trends, offering an active tool to track public opinion.

5.4 Limitations:

5.4.1. Model Generalization: Models trained on reviews of one type (e.g., electronics) do not generalize to another type (e.g., fashion).

5.4.2. Internet Dependency: Because Firebase and scraping are internet-dependent, the system is not accessible offline.

5.4.3. Restricted Multilingual Ability: Multilingual preprocessing has been tried, but actual multilingual sentiment training has not been done.

5.4.4. Scope of Aspect-Level Analysis: Although ABSA (Aspect-Based Sentiment Analysis) is mentioned, it needs to be clarified in terms of understanding more important aspects such as comments on battery life vs. comments on screen quality.

References:

[1] *G. K. Patra, C. Kuraku, S. Konkimalla, V. N. Boddapati, M. Sarisa, S. K. Rajaram, M. S. Reddy and K.*

Polimetla, "A Sentiment Analysis of Customer Product Review Based on Machine Learning Techniques in E-Commerce," Journal of Artificial Intelligence & Cloud Computing, ISSN: 2754-6659. [Online]. Available: Open Access.

[2] *M. Loukili, F. Messaoudi, and M. El Ghazi, "Sentiment Analysis of Product Reviews for E-Commerce Recommendation Based on Machine Learning," Int. J. Advance Soft Compu. Appl., vol. 15, no. 1, pp. [page range], Mar. 2023, doi: 10.15849/IJASCA.230320.01.*

[3] *S. Yi and X. Liu, "Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review," Complex & Intelligent Systems, vol. 6, pp. 621–634, 2020, doi: 10.1007/s40747-020-00155-2.*

[4] *R. Thomas and J. R. Jeba, "A novel framework for an intelligent deep learning based product recommendation system using sentiment analysis (SA)," Automatika, vol. 65, no. 2, pp. 410–424, 2024, doi: 10.1080/00051144.2023.2295148.*

[5] *S. S. Sohail, J. Siddiqui, and R. Ali, "Feature extraction and analysis of online reviews for*

the recommendation of books using opinion mining technique," Perspectives in Science,

vol. 8, 2016, doi: 10.1016/j.pisc.2016.06.079.

[6] *J. Ye, J. Hai, J. Song, and Z. Wang, "Multimodal Data Hybrid Fusion and Natural Language Processing for Clinical Prediction Models," medRxiv, preprint, Aug. 25, 2023. doi: 10.1101/2023.08.24.23294597.*

[7] *N. Malik and M. Bilal, "Natural language processing for analyzing online customer reviews: a survey, taxonomy, and open research challenges," PeerJ Comput. Sci., vol. 2024, Art. no. e2203, Jul. 2024, doi: 10.7717/peerj-cs.2203.*

[8] *C. N. Dang, M. N. Moreno-García, and F. D. la Prieta, "An Approach to Integrating Sentiment Analysis into Recommender Systems," Sensors, vol. 21, no. 16, Art. no. 5666, Aug. 2021, doi: 10.3390/s21165666.*

[9] *Preethi, G.; Krishna, P.V.; Obaidat, M.S.; Saritha, V.; Yenduri, S. Application of Deep Learning to Sentiment Analysis for RecomMender System on Cloud. In Proceedings of the 2017 International Conference on Computer, Information and Telecommunication Systems (CITS), Dalian, China, 21–23 July 2017; IEEE: New York, NY, USA, 2017; pp. 93–97.*

[10] *Acharya N, Sassenberg AM, Soar J. 2024. Effects of cognitive absorption on continuous use intention of AI-driven recommender systems in e-commerce. Foresight 25(2):194–208 DOI 10.1108/FS-10-2021-0200.*

[11] *Al-Ghuribi S, Noah SAM, Mohammed M. 2023. An experimental study on the performance of collaborative filtering based on user reviews for large-scale datasets. PeerJ Computer Science 9(3):e1525 DOI 10.7717/peerj-cs.1525.*

[12] *Jianqiang Z, Xiaolin G, Xuejun Z (2018) Deep convolution neural networks for twitter sentiment analysis. IEEE Access 6:2325323260. https://doi.org/10.1109/ACCESS.2017.2776930.*

[13] *Jianqiang Z, Xiaolin G (2017) Comparison research on text preprocessing methods on twitter sentiment analysis. IEEE Access 5:2870–2879. https://doi.org/10.1109/ACCESS.2017.267267.*

[14] *Olagunju T, Oyebode O, Orji R. Exploring key issues affecting African mobile ecommerce applications using sentiment and thematic analysis. IEEE Access.2020;8:114475–114486.doi:10.1109/ACCESS.2020.3000093.*

[15] *Ricci F, Rokach L, Shapira B. Recommender systems handbook. Vol. XVIINew York (NY): Springer; 2010.p.1003. doi:10.1007/978-1-4899-7637-6.*

[16]*ZhangJ,ChenD,LuM.Combiningsentimentanalysis with a Fuzzy Kano model for product aspect preference recommendation. IEEE Access. 2018;6:59163–59172.*

doi:10.1109/ACCESS.2018.2875026.

[17] *Trilla A, Alias F (2013) Sentence-based sentiment analysis for expressive text-to-speech. IEEE Trans Audio Speech Lang Process*

21(2):223–233. https ://doi.org/10.1109/TASL.2012.22171 29.

[18] *Devi DGL, Vallabhaneni SP, Singothu DJR. Performance evaluation of DLSARS framework in intelligent product recommendation systems;2020. Available from SSRN: doi:10.2139/ssrn.3738862.*

[19] *Puerta Melguizo MC, Boves L, Deshpande A, et al. A proactive recommendation system for writing: Helping without disrupting. Proceedings of the 14th European conference on Cognitive ergonomics: invent! explore!.2007: 89–95. doi:10.1145/1362550.1362569.*

[20] *Li M, Wu H, Zhang H. Matrix factorization for personalized recommendation with implicit feedback and temporal information in social ecommerce networks. IEEE Access. 2019;7:141268–141276. doi:10.1109/ACCESS.2019.2943959.*

[21] *Khanvilkar G, Vora D. Sentiment analysis for product recommendation using random forest. Int J Eng Technol. 2018;7(3):87–89. doi:10.14419/ijet.v7i3.3.14492.*

[22] *Lutz B, Pröllochs N, Neumann D. 2022. Are longer reviews always more helpful? Disentangling the interplay between review length and line of argumentation. Journal of Business Research 144(11):888–901 DOI 10.1016/j.jbusres.2022.02*