AI-Powered Product Review Analytics and Ranking Dashboard System

Ms. D. Bhavana[1] K. Sai Kiran[2] K. Nitheesh[3] K. Yugendhar[4] K.Venkata Karthik[5]
[1,2,3,4,5]Department of Computer Science and Engineering
[1,2,3,4,5]Bharath Institute of Higher Education and Research, Chennai, India

Abstract — AI-Powered Product Review Analytics and Ranking Dashboard System integrates Natural Language Processing (NLP), Machine Learning (ML), Java, and SQL database ranking mechanisms to automate customer feedback analysis and improve product evaluation. The framework is designed to overcome the limitations of manual review analysis and traditional rating-based systems in modern e-commerce environments. When customers submit reviews, the system analyzes the textual content using NLP techniques such as preprocessing, tokenization, stop-word removal, normalization, and vectorization to classify feedback into Positive, Negative, or Neutral sentiment categories. Based on the predicted sentiment, a weighted scoring algorithm dynamically updates product rankings in an SQL database. The system provides an intelligent, scalable, and real-time solution that enhances user experience and supports business decision-making by promoting highly rated products, reducing the visibility of poorly reviewed products, and identifying re currying issues through sentiment insights. This approach improves transparency, ranking accuracy, and overall product quality management in both online and offline retail environments.

Keywords: Artificial Intelligence, NLP, Sentiment Analysis, E- commerce, Java, SQL, Customer Reviews, Product Ranking, Machine Learning, Dashboard Analytics

I. INTRODUCTION

The rapid growth of e-commerce platforms has significantly transformed customer purchasing behavior, making product reviews one of the most influential factors in decision-making.

Consumers often depend on online feedback to evaluate product quality, reliability, and overall satisfaction before making purchases. As the number of customer reviews increases daily, manually analyzing such massive feedback becomes difficult, time-consuming, and inefficient. Traditional ranking systems mainly depend on star ratings and review counts, which fail to capture the actual sentiment and emotional intensity expressed in textual reviews. A product may receive a high rating while containing negative comments regarding quality, durability, or service. Such limitations create inaccurate rankings and reduce customer trust. To solve this issue, the proposed AI-Powered Product Review Analytics and Ranking Dashboard System introduces an intelligent framework that combines Artificial Intelligence techniques such as Natural Language Processing (NLP), Machine Learning (ML), Java backend processing, and SQL database mechanisms.

The system automatically processes customer reviews using tokenization, stop-word removal, normalization, and vectorization techniques such as TF-IDF. Machine learning models classify reviews into Positive, Negative, or Neutral sentiments. Based on sentiment results, a dynamic weighted scoring algorithm updates product rankings in real time. Products with strong positive sentiment gain higher visibility, while negatively reviewed products are ranked lower or flagged for quality review. This intelligent system improves ranking accuracy, supports business decision-making, enhances customer trust, and creates a scalable solution for modern e-commerce environments.

II. OBJECTIVE

The primary objective of the AI-Powered Product Review Analytics and Ranking Dashboard System is to develop an intelligent framework that automatically analyzes customer feedback and improves product ranking mechanisms in modern e-commerce platforms. The system is designed to overcome the limitations of traditional rating- based methods by integrating Artificial Intelligence, Natural Language Processing (NLP), Machine Learning (ML), Java backend technologies, and SQL database systems. The specific objectives of the proposed system are as follows: Data Collection and Review Management: To collect customer product reviews, ratings, and feedback through a user-friendly web interface and store the information efficiently in a structured SQL database. Text Preprocessing: To clean and prepare raw review data using NLP techniques such as tokenization, stop-word removal, stemming, lemmatization, and normalization to improve data quality and model performance. Feature Extraction and Vectorization: To convert unstructured textual reviews into numerical representations using techniques such as TF-IDF, Bag-of-Words, or Word2Vec for effective machine learning analysis.

- Sentiment Classification: To implement machine learning algorithms capable of accurately classifying customer reviews into Positive, Negative, and Neutral sentiment categories.
- Dynamic Product Ranking: To design a weighted scoring algorithm that combines sentiment polarity with product ratings and updates product rankings dynamically in real time.
- Dashboard Analytics: To develop an interactive dashboard that visually presents sentiment trends, ranking reports, product performance metrics, and customer opinion distribution using graphs and charts.
- Decision Support System: To help businesses identify product strengths, recurring customer complaints, and improvement opportunities through automated review intelligence.
- Scalability and Efficiency: To ensure that the system can handle large volumes of customer reviews with low latency and high processing efficiency for practical deployment.
- Customer Trust Enhancement: To improve transparency and user confidence by presenting rankings based on real customer opinions rather than static numerical averages.
- Future Expansion Capability: To create a modular system that can later support multilingual sentiment analysis, fraud review detection, recommendation systems, and cloud deployment.

III. LITERATURE SURVEY

The rapid growth of e-commerce platforms has increased the importance of customer reviews as a major source of information for both consumers and businesses. Researchers and industries have explored various methods to analyze reviews, predict customer sentiment, and improve product recommendation systems. Existing studies mainly focus on three major areas: text representation techniques, sentiment classification models, and product ranking systems.

A. Text Representation Techniques

One of the fundamental challenges in review analysis is converting unstructured textual data into machine-readable numerical form. Early research widely used traditional feature extraction techniques such as Bag-of-Words (BoW) and Term Frequency Inverse Document Frequency (TF-IDF). These methods measure word frequency and importance within documents, making them computationally efficient and suitable for basic sentiment tasks. However, they often fail to capture semantic relationships and contextual meaning between words. To overcome these limitations, advanced vectorization approaches such as Word2Vec, GloVe, and embedding-based models were introduced. These methods generate dense numerical vectors that preserve semantic similarity between words. For example, words such as excellent and fantastic are represented closely in vector space. Such approaches improve sentiment prediction accuracy and enhance natural language understanding.

B. Sentiment Classification Models

Many studies have applied machine learning algorithms for customer review sentiment classification. Traditional classifiers such as Naive Bayes, Logistic Regression, and Support Vector Machines (SVM) are widely used because of their speed, simplicity, and good performance on balanced datasets. These models classify reviews into categories such as Positive, Negative, or Neutral based on learned patterns from training data. Recent research has shifted toward deep learning techniques such as Recurrent Neural Networks (RNNs), Long Short- Term Memory (LSTM) networks, and transformer-based models such as BERT. These methods capture contextual dependencies and sequential relationships in text, leading to higher accuracy. However, they require large computational resources, higher training time, and increased deployment complexity.

C. Product Ranking and Recommendation Systems

Traditional e-commerce product ranking systems mainly depend on numerical metrics such as star ratings, review count, popularity score, and sales volume. While these methods are easy to implement, they fail to reflect the actual sentiment expressed in textual feedback. A product with high ratings may still contain repeated negative complaints regarding durability, packaging, or customer support. Some modern systems attempt to integrate sentiment scores into ranking mechanisms, but many operate as decoupled systems where sentiment analysis is performed separately and later updated in batches. This creates delays and reduces real- time responsiveness.

D. Research Gap and Proposed Contribution

The literature indicates that although advanced sentiment analysis methods exist, there is limited research on integrating real-time AI- based review analytics directly with product ranking systems in a scalable Java-SQL environment. Most existing systems e ither focus only on classification accuracy or rely on static ranking methods. The proposed AI-Powered Product Review Analytics and Ranking Dashboard System addresses this gap by combining NLP preprocessing, machine learning sentiment analysis, dynamic weighted ranking algorithms, and dashboard visualization within a unified platform. The system ensures that product rankings instantly reflect customer sentime nt, thereby improving ranking transparency, customer trust, and business decision-making.

IV. WORKING OF THE PROPOSED SYSTEM

The proposed AI-Powered Product Review Analytics and Ranking Dashboard System is designed as an intelligent framework that automates customer feedback analysis and dynamically ranks products based on real-time sentiment extracted from reviews. The system integrates Artificial Intelligence, Natural Language Processing (NLP), Machine Learning (ML), Java backend processing, and SQL database technologies to create a scalable and efficient solution for modern e-commerce platforms. Unlike traditional systems that rely only on star ratings or review counts, the proposed model considers the actual sentiment expressed in textual feedback, thereby providing more accurate product visibility and ranking.

A. Customer Review Collection

The first stage of the system involves collecting product reviews and ratings from users through a web-based interface. Customers can browse products, select items, and submit textual feedback along with numerical ratings. These reviews are stored in a structured SQL database for further processing. This stage ensures continuous data acquisition and real-time user interaction.

B. Text Preprocessing

The submitted reviews are usually unstructured and may contain spelling errors, punctuation, unnecessary words, or inconsistent formatting. Therefore, the system applies standard NLP preprocessing techniques such as tokenization, stop-word removal, normalization, stemming, and lemmatization. These steps clean the raw data and improve the quality of textual input before classification.

C. Feature Extraction and Vectorization

After preprocessing, the cleaned textual reviews are transformed into numerical vectors using feature extraction methods such as TF- IDF, Bag-of-Words, or Word2Vec. These techniques convert text into machine-readable format while preserving important word frequency and semantic relationships. The resulting feature vectors are used as input for machine learning classifiers.

D. Sentiment Classification:

The system employs machine learning algorithms such as Logistic Regression, Naive Bayes, or Support Vector

Machine (SVM) to classify customer reviews into three sentiment categories: Positive Negative Neutral Each review is analyzed automatically, and a sentiment label is assigned based on its textual content. This process eliminates manual review analysis and provides accurate feedback interpretation.

E. Dynamic Product Ranking Mechanism:

Once the sentiment is predicted, the system assigns a Weighted Polarity Score (Wp) to the review. For example: Positive = +1 Neutral = 0 Negative =-1 The score is combined with product ratings and historical feedback data. A ranking algorithm running in the SQL database recalculates product rankings dynamically whenever a new review is submitted. Products with consistently positive reviews move higher i n rank, while poorly reviewed products are demoted or flagged for quality control.

F. Dashboard Analytics and Reporting:

The processed data is displayed through an interactive dashboard. The dashboard provides visual insights such as: Sentiment distribution charts Top ranked products Review trends over time Positive vs Negative ratio Product performance reports This allows businesses to understand customer opinions quickly and make informed decisions.

G. Advantages of the Proposed System:

The proposed system offers several advantages over traditional ranking methods: Real-time sentiment-based product ranking Improved ranking accuracy and fairness Reduced manual effort in review analysis Better customer trust and transparency Quick identification of poor-quality products Scalable architecture for large review datasets Thus, the proposed AI-powered system transforms ordinary customer reviews into valuable business intelligence and creates a modern, data-driven ranking platform for e-commerce applications.

V. SYSTEM ARCHITECTURE

The AI-Powered Product Review Analytics and Ranking Dashboard System is designed using a multi-layered architecture that ensures scalability, flexibility, real-time processing, and efficient communication between system components. The architecture integrates frontend technologies, backend business logic, machine learning models, and SQL database mechanisms into a unified framework. This structured design enables smooth data flow from customer review submission to sentiment analysis, dynamic ranking, and dashboard reporting. The system architecture is divided into three major layers: Presentation Layer, Application Layer, and Data Layer. Each layer performs specific tasks and collectively supports intelligent product review analytics.

A. Presentation Layer

The Presentation Layer represents the user interface through which customers and administrators interact with the system. It is developed using HTML, CSS, JavaScript, and responsive web technologies. The key functions of this layer include: Displaying available products to customers Allowing users to submit textual reviews and ratings Showing ranked product lists Presenting dashboard charts and reports Providing login and administrative control features This layer acts as the communication bridge between users and the analytical engine. It ensures a user-friendly experience for both customers and business managers.

B. Application Layer

The Application Layer is the core processing unit of the system and is developed using Java and Spring Boot technologies. This layer handles all business logic, review processing, sentiment prediction, and ranking
operations. Its major responsibilities include:

1) Review Ingestion Module Receives customer reviews from the frontend and validates the input data.
2) NLP Processing Module Performs text preprocessing such as tokenization, stop-word removal, stemming, lemmatization, and normalization.
3) Vectorization Module Converts cleaned reviews into numerical vectors using TF-IDF, Bag-of-Words, or Word2Vec techniques.
4) Sentiment Classification Module Uses machine learning algorithms such as Logistic Regression, Naive Bayes, or SVM to classify reviews into Positive, Negative, or Neutral sentiment classes.
5) Ranking Engine Assigns Weighted Polarity Scores and updates product rankings dynamically based on sentiment
6) output and customer ratings.
7) Dashboard Service Module Fetches processed data and generates reports, charts, and analytics for visualization. The Application Layer serves as the intelligence center of the system, where AI-driven decisions are made automatically.

C. Data Layer

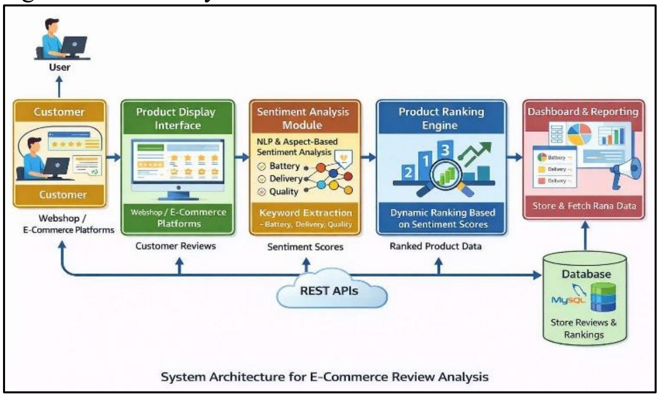
The Data Layer consists of the MySQL / SQL database used for persistent storage and ranking computation. It stores all product details, customer reviews, sentiment results, ranking scores, and historical analytics data. The database contains tables such as: Product Table Review Table Sentiment Result Table Ranking Table User Table Stored procedures and SQL queries are used to update rankings efficiently in real time whenever new reviews are submitted.

D. Workflow of the Architecture The complete system workflow is as follows:

1) Customer submits product review and rating. 2. Review is sent to Java backend.
2) NLP preprocessing cleans the text.
3) Vectorization converts text into numerical form. 5. Machine learning model predicts sentiment.
4) 6. Weighted score is generated.
5) 7. SQL ranking engine updates product rank.
6) 8. Dashboard displays updated rankings and analytics.

E. Advantages of the Architecture Modular and scalable design

Real-time review processing Easy integration with e-commerce platforms Efficient database communication using JDBC Supports future AI model upgrades High performance for large review datasets Thus, the proposed architecture provides a robust foundation for intelligent product ranking and review analytics, ensuring efficient operation in modern digital commerce systems.



System Architecture for E-Commerce Review Analysis

VI. EXISTING SYSTEM

The existing product review and ranking systems used in most e-commerce platforms are primarily based on simple numerical indicators such as average star ratings, review counts, popularity scores, and sales volume. These methods are widely adopted because they are easy to implement and require minimal computational resources. However, despite their simplicity, such systems have several major limitations when it comes to accurately representing true customer satisfaction and product quality. In traditional platforms, customer feedback is generally summarized using star ratings from one to five. Products with higher average ratings are displayed at the top of search results or recommendation lists.

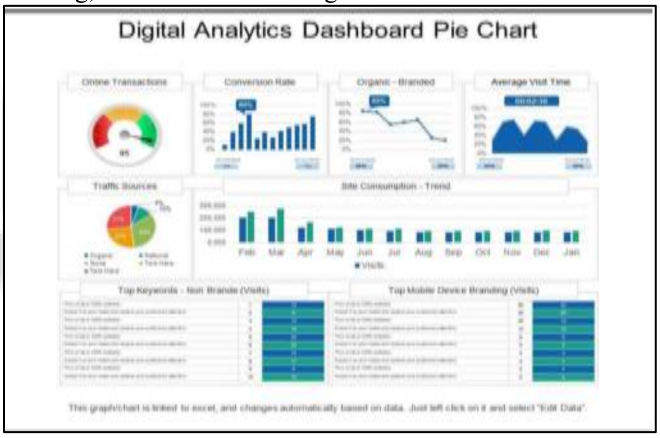
While this method provides a quick measure of popularity, it ignores the detailed textual opinions written by customers.

For example, a product may receive a five-star rating while the written review mentions issues such as delayed delivery, poor packaging, or low durability. Since the system only con siders the rating value, such hidden negative feedback remains unnoticed. Another common ranking factor in existing systems is the number of reviews. Products with a higher review count are often considered more trustworthy and are ranked above newer products. However, this creates an unfair advantage for older products and makes it difficult for recently launched high- quality products to gain visibility. A new product with fewer but highly positive reviews may still rank below an older product with thousands of average or neutral reviews. Some platforms use time-based ranking or popularity trends to reorder products periodically.

Although these approaches improve freshness, they still fail to analyze the emotional intensity and meaning present in review text. A severely negative recent review may not significantly affect product rank if the historical star average remains high. This delays corrective action and can reduce customer trust. A few modern systems apply basic sentiment analysis, usually limited to binary or ternary classes such as Positive, Negative, or Neutral. While this is an improvement over rating-only methods, these systems still do not capture the degree of emotion. Reviews such as good and absolutely amazing may both be treated as Positive, even though their impact should differ. Similarly, bad and completely terrible may receive the same Negative label. Another major drawback of many existing systems is delayed data synchronization. In several implementations, sentiment analysis is performed separately from the ranking engine, and results are updated in batches after several hours or days. This creates latency between customer feedback and ranking changes. As a result, product rankings may not reflect the latest customer experiences in real time. The existing systems also provide limited analytical dashboards. Most platforms only display star averages and total reviews, offering little insight into sentiment trends, recurring complaints, or comparative product performance. Businesses therefore lose valuable opportunities for quality improvement and customer retention.

Overall, the traditional product ranking systems suffer from the following limitations: Dependence on average star ratings only Ignoring detailed textual sentiment in reviews Unfair preference to older products with more reviews No real-time ranking updates Inability to detect emotional intensity of opinions Limited dashboard analytics and reporting Slow response to product quality issues These limitations highlight the need for an intelligent AI-based framework that can analyze textual reviews, detect sentiment accurately, and dynamically update product rankings.

The proposed AI-Powered Product Review Analytics and Ranking Dashboard System is designed to overcome these drawbacks by integrating NLP, machine learning, and real- time ranking mechanisms.



VII. PROBLEM STATEMENT

The rapid expansion of e-commerce platforms has made product ranking systems a critical component in influencing customer purchase decisions. Most online marketplaces rely on product visibility mechanisms such as average star ratings, review counts, popularity indexes, and historical sales performance to determine which products are displayed prominently. Although these approaches are widely used, they suffer from major limitations because they do not accurately reflect the real sentiment and detailed opinions expressed by customers in textual reviews. As a result, many ranking systems fail to provide a trustworthy representation of actual product quality and customer satisfaction. One of the primary problems with existing systems is the excessive dependence on numerical star ratings. A product may receive a high rating while customers mention serious issues in written feedback such as poor durability, defective components, delayed delivery, or weak customer support. Since conventional ranking algorithms mainly consider numerical averages, these hidden negative experiences are ignored. This creates misleading product visibility and may encourage customers to purchase lower-quality products. Another major issue is the use of review count as a ranking factor. Older products with a large number of average or neutral reviews often dominate search results, while newer products with fewer but highly positive reviews struggle to gain visibility.

This creates an unfair competitive environment and limits opportunities for innovative or recently launched products. The current systems also lack the ability to understand the emotional intensity of customer opinions. Reviews such as good product and absolutely outstanding product with excellent quality may both be treated equally as positive feedback. Similarly, mildly negative comments and extremely dissatisfied reviews may receive the same negative weight.

This inability to measure sentiment intensity results in inaccurate ranking decisions. Another significant problem is the absence of real-time feedback integration. In many platforms, review analysis and ranking updates occur periodically in batches rather than instantly. Consequently, newly submitted positive or negative reviews do not immediately influence product rankings. Products receiving repeated recent complaints may continue appearing at the top, reducing customer trust and damaging platform credibility. Businesses also face difficulties in extracting actionable insights from massive volumes of unstructured review data. Manual analysis of customer feedback is time- consuming, inconsistent, and impractical for large-scale systems.

Without automated analytics, organizations may fail to detect recurring quality issues, service complaints, or changing customer preferences in time. Therefore, there is a strong need for an intelligent product ranking framework that can automatically process textual reviews, identify customer sentiment accurately, assign weighted scores based on sentiment intensity, and dynamically update rankings in real time. The proposed AI-Powered Product Review Analytics and Ranking Dashboard System addresses this problem by integrating Natural Language Processing (NLP), Machine Learning (ML), Java backend technologies, and SQL database ranking mechanisms. The system converts textual customer feedback into sentiment intelligence and ensures that prod uctvisibility reflects real customer opinions rather than static numerical averages.

This leads to more accurate rankings, improved customer trust, and better business decision-making.

VIII. Conclusion

The implementation of the AI-Powered Product Review Analytics and Ranking Dashboard System successfully addresses the major limitations of conventional product ranking methods by introducing an intelligent, dynamic, and sentiment- driven evaluation framework. Traditional e-commerce systems mainly depend on average star ratings, review counts, an d historical popularity, which often fail to capture the actual opinions, emotional intensity, and contextual meaning present in customer reviews. The proposed system overcomes these drawbacks by integrating Artificial Intelligence techniques such as Natural Language Processing (NLP), Machine Learning (ML), Java backend processing, and SQL database ranking mechanisms into a unified platform. The system demonstrates that customer reviews contain valuable business intelligence that can be transformed into meaningful insights through automated analysis. By applying preprocessing techniques such as tokenization, stop-word removal, normalization, a nd vectorization, unstructured textual data is converted into machine-readable form. Machine learning algorithms then classify reviews into Positive, Negative, or Neutral sentiments with high efficiency.

This automated process significantly reduces the time, effort, and inconsistency associated with manual review analysis. One of the most significant achievements of the system is the implementation of a dynamic ranking mechanism based on Weighted Polarity Scores. Unlike static ranking models, the proposed framework ensures that each newly submitted review immediately influences product visibility. Products receiving strong positive feedback are promoted in rankings, while poorly reviewed products are demoted or flagged for quality control. This real-time feedback loop creates a more transparent and trustworthy environment for customers. The system also enhances decision-making for businesses by providing dashboard analytics such as sentiment trends, ranking reports, customer opinion distribution, and recurring complaint detection. These insights help organizations identify product strengths, improve weak areas, optimize marketing strategies, and respond quickly to changing customer preferences. From a technical perspective, the modular architecture of the system ensures scalability, maintainability, and efficient integration with existing e-commerce platforms. The use of Java and SQL technologies provides reliable backend performance and real- time data management, making the system suitable for large- scale deployment.

In conclusion, the proposed AI-powered framework successfully transforms traditional product ranking systems into intelligent decision-support systems.It improves ranking accuracy, customer trust, business responsiveness, and overall user experience. The project demonstrates the practical importance of combining AI with real-world commerce applications and provides a strong foundation for future advancements in sentiment-driven analytics and automated ranking systems.

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