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Product Rating System Using Deep Neural Network

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ABSTRACT

Online shopping has grown rapidly, and customer ratings play a big role in helping people decide what to buy. However, traditional ratings can sometimes be inconsistent or unreliable. To fix this, the proposed system uses AI and text analysis to automatically read customer reviews and generate accurate product ratings.

Instead of asking customers to manually pick a star rating, this system reads the actual words in a review and figures out how positive or negative it is. This makes the ratings more honest and consistent.

The final product is a simple website where users can type in their review for a product. Once submitted, the system reads the review, understands its tone, and gives it a score from 1 to 5. When multiple reviews are collected, all the scores are combined to create one overall rating that truly reflects what customers think about the product.

Keywords - Product Rating System, Sentiment Analysis, Deep Learning, NLP, Customer Reviews, Long Short Term Memory (LSTM), Convolutional Neural Networks (CNN), Automated Rating, E-commerce.

I. INTRODUCTION

The rapid rise of e-commerce in today's digital world has resulted in a huge amount of online product review data being generated every day. These reviews have become a key resource for consumers, who heavily depend on them to assess product quality and reliability before making a purchase. However, the current system of online feedback comes with several serious problems. Traditional rating systems rely too much on manually assigned star ratings, which are often influenced by personal bias, inconsistency, and in some cases, deliberate manipulation. On top of that, the enormous volume of textual data makes it nearly impossible for consumers or businesses to analyze everything manually in a practical and time-efficient way.

To overcome these challenges, there is a clear and growing demand for automated systems that can objectively understand and interpret customer opinions at scale. Recent breakthroughs in Artificial Intelligence (AI) and Natural Language Processing (NLP) have opened the door to powerful tools capable of extracting meaningful insights directly from raw text. A core technology driving this progress is Sentiment Analysis, which enables computational systems to detect attitudes, emotions, and specific feedback — whether positive, negative, or neutral — present within a customer review.

Modern Sentiment Analysis approaches are increasingly built around Deep Learning architectures, including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN). These models are highly effective at recognizing complex linguistic patterns and understanding the contextual relationships between words — something that traditional machine learning methods often struggle to capture accurately.

This project presents an intelligent, web-based Product Rating System built using Python and deep learning libraries. By processing customer review data from sources like the Amazon product review dataset, the system predicts sentiment and automatically generates a consistent numerical rating on a scale of 1 to 5. This approach delivers a more transparent, reliable, and data-driven method of evaluating products, ultimately building greater user trust within the e-commerce environment.

II. RELATED WORK

Sentiment analysis and product rating prediction have been widely studied in the fields of Natural Language Processing (NLP) and deep learning. Researchers have proposed various approaches to analyze customer reviews and automatically generate ratings for e-commerce platforms.

Initial sentiment analysis studies mainly used machine learning approaches including Naïve Bayes, Support Vector Machines, and Logistic Regression to classify review sentiment. These models used feature extraction techniques such as bag-of-words (BoW) and Term Frequency–Inverse Document Frequency (TF-IDF). Although these methods achieved reasonable performance, they required manual feature engineering and failed to capture the deep contextual relationships between words. Consequently, their effectiveness decreased when handling large-scale datasets and complex sentence structures.

With the advancement of deep learning, researchers have begun applying neural network architectures to sentiment classification tasks. Hassan and Shoaib (2020) proposed a multi-class review rating classification system using Deep Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models. These models can learn sequential dependencies in textual data, allowing them to understand the contextual meaning across sentences. Their approach significantly improved classification accuracy compared to traditional machine learning models, especially for multi-class rating prediction problems.

Similarly, Smetanin and Komarov (2019) applied Convolutional Neural Networks (CNNs) for sentiment analysis of product reviews. CNN models automatically extract high-level textual features using convolutional filters, reducing the need for manual feature engineering. Their research demonstrated that CNN-based models are efficient for identifying sentiment patterns within sentences and achieving strong performance in text classification tasks. However, CNNs may sometimes struggle to capture long-range dependencies compared to recurrent models.

In addition to sentiment classification, recommendation systems incorporate deep learning techniques. Katarya and Arora (2020) introduced CapsMF, a deep learning–based product recommendation framework that combines text analysis with collaborative filtering. Their system utilized capsule networks to extract meaningful product and user features from textual reviews, thereby improving personalized recommendations. This study highlights the importance of integrating sentiment analysis with recommendation systems to enhance user satisfaction.

Another critical area of research is the detection of fake reviews. Hajek et al. (2020) proposed a deep neural network model that integrates word embeddings and emotion mining techniques to detect fraudulent reviews. Their study emphasized that fake reviews can distort product ratings and mislead consumers. By identifying and filtering misleading content, their approach improved the reliability and trustworthiness of online rating systems.

Ahmed and Ghabayen (2022) developed a review rating prediction framework using deep learning architectures. Their system analyzed textual reviews and directly predicted numerical rating values. This approach reduced dependency on manually assigned star ratings and improved rating consistency. This study demonstrated that automated rating prediction models provide more objective and standardized product evaluations.

Furthermore, recent advancements in transformer-based architectures such as BERT have shown state-of-the-art performance in sentiment analysis tasks. Transformer models utilize attention mechanisms to capture contextual relationships more effectively than traditional recurrent neural network-based models. Although these models achieve high accuracy, they require significant computational resources, which may limit their deployment in real-time applications.

Despite substantial progress in this domain, existing research has certain limitations. Many systems focus primarily on sentiment classification without implementing real-time rating-aggregation mechanisms. Some approaches lack scalability for integration with large e-commerce platforms. In additionally, few studies have combined sentiment analysis, automated rating generation, and web-based deployment into a unified framework.

The proposed Product Rating System using Deep Neural Network builds upon these prior works by integrating advanced sentiment analysis models with automatic rating prediction and aggregation. The system ensures real-time rating updates, reduces human bias, and provides a scalable web-based application suitable for modern e-commerce environments. By combining deep learning techniques with practical deployment strategies, the proposed system aims to enhance transparency, reliability, and user trust in online product evaluation systems.

III. PROPOSED WORK

The proposed work aims to build an intelligent Product Rating System that automatically reads customer reviews and generates accurate product ratings using Deep Neural Network techniques. Unlike traditional systems that depend entirely on manually assigned star ratings, the proposed system focuses on extracting sentiment and meaningful insights from the text of reviews to produce unbiased and more reliable ratings.

The system allows users to submit their product reviews through a simple online interface, where they are stored for further analysis. All submitted reviews are saved in a centralized database and prepared for the next stage of processing. During the preprocessing stage, Natural Language Processing (NLP) techniques such as tokenization, stop-word removal, stemming, and text normalization are applied to clean and organize the raw textual data properly.

Once preprocessing is complete, the cleaned text is converted into numerical representations using word embeddings. A deep learning model, such as LSTM, CNN, or RNN, is then applied to analyze the contextual meaning within the review and predict its sentiment. Based on the sentiment score produced by the model, the system automatically assigns a rating value on a predefined scale of 1 to 5.

The individually predicted ratings are then aggregated together to calculate the overall product rating. The system continuously updates these ratings in real time and presents the results on a web-based dashboard. This process effectively reduces human bias, improves the overall accuracy of ratings, and helps build greater customer trust in the platform.

Furthermore, the proposed system is designed to be scalable and can be integrated with existing e-commerce platforms to handle large volumes of review data without performance issues. By combining sentiment analysis, automated rating generation, and real-time deployment into one framework, the proposed model delivers a smarter and more dependable product evaluation system.

To represent text in a form that deep learning models can process, the cleaned reviews are transformed into numerical vectors using word embedding techniques such as Word2Vec. These vector representations allow deep neural networks to better understand the contextual meaning of words within a review. The core component of the system is the Deep Learning Model, which may use architectures such as LSTM, GRU, CNN, or Bidirectional LSTM. These models are effective at capturing sequential patterns and contextual dependencies present in textual data, enabling highly accurate sentiment prediction.

Based on the sentiment score predicted by the model, the system automatically assigns a rating on a scale of 1 to 5. Rather than depending solely on stars given by users, the rating is produced by analyzing the emotional tone and contextual meaning of the actual review text. The predicted ratings gathered from multiple reviews are then aggregated to dynamically compute one overall product rating.

The proposed system also supports real-time rating updates, which means that every time a new review is submitted, the overall product rating is immediately recalculated. This ensures that the rating displayed always reflects the most current customer opinion. The system can also be further strengthened with fake review detection mechanisms to improve the authenticity and trustworthiness of the generated ratings.

The proposed method is fully scalable and capable of efficiently managing large volumes of review data. It can be smoothly integrated with existing e-commerce platforms to provide automated, transparent, and reliable rating generation. By bringing together NLP techniques, deep learning algorithms, and web-based deployment, the system improves the overall user experience, supports better and more informed purchasing decisions, and increases trust in online marketplaces.

IV. EXPERIMENTAL RESULT

This work takes into account the Amazon product review dataset and creates an RNN model in order to assess the suggested mechanism. Finding efficient product promotion through ratings and reviews is the main objective. The review, which includes some witty comments from program users, should be noted during analysis. Before installing or using the application, most people like to read through the reviews left by other users. The review metrics accuracy, precision, recall, and f1 score are employed to gauge the suggested system's effectiveness. Table 1shows Performance factors of proposed system. In figure 2 Performance metrics comparisons

A. Accuracy

The general validity of the model predictions was gauged by its accuracy. Out of all the examples in the dataset, it provides the percentage of correctly classified cases. It is crucial to remember that accuracy alone might not be adequate in every situation, particularly when working with imbalanced datasets, where one class is significantly more common than the other. For a more thorough analysis under such circumstances, further measures, including precision, recall, and F1, score may be employed.

$$Accuracy=\frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad (1)$$

B. Precision

High precision means that the model can effectively filter out false positives. But accuracy by itself might not provide a complete picture of a model's performance, particularly when false negatives—instances that were positive but expected to be negative—also play a significant role.

When the model predicts positively and those forecasts are probably accurate, precision is high. False positives can affect precision; if the model predicts too many false positives, precision will suffer.

$$Precision= \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (2)$$

C. Recall

The model's recall refers to its capacity to detect or identify every pertinent instance of a positive class. "Of all the actual positive instances, how many did the model correctly identify?" is the question it answers. In contrast, a low recall

implies that a sizable portion of positive cases is being missed by the model, whereas a high recall indicates that the model is good at catching the majority of positive occurrences. When the cost of overlooking a positive instance (false negative) is considerable and it is imperative to reduce such cases, recall plays a critical role

$$\text{Recall}= \frac{\text{True Positives}}{\text{True Positives + False Negatives}} \quad (3)$$

D.F1-Score

The binary classification model with a high F1 score performed well overall. This shows that the model can minimize false positives and false negatives while efficiently identifying positive cases. The Performance of the proposed system was evaluated using standard evaluation metrics such as accuracy, precision, recall, and F1-score. Please, use the button below to paraphrase. It really is that simple

$$\text{F1−Score}=\frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision + Recall}} \quad (4)$$

Table -1 Performance factors of proposed system

Metrics	Value
Accuracy	0.8896
Precision	0.8755
Recall	0.9090
F1 Score	0.9819

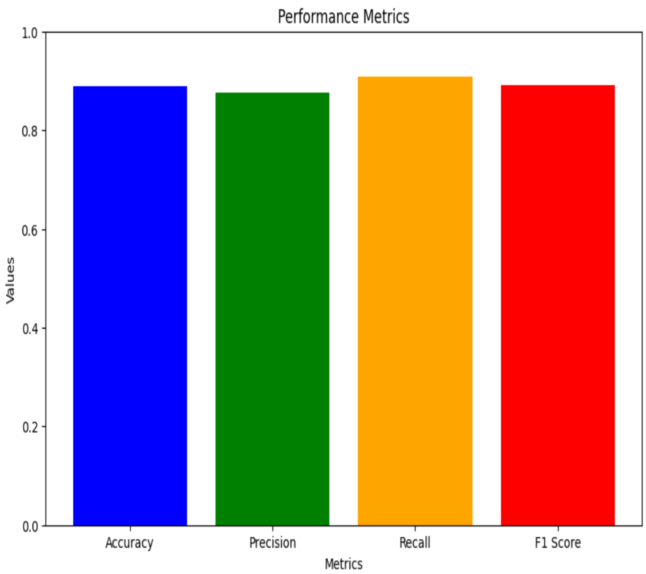

Fig. 3. Performance metrics comparisons

V. CONCLUSION

The proposed **Product Rating System Using Deep Neural Network** successfully demonstrates how Artificial Intelligence and Natural Language Processing can enhance product evaluation on e-commerce platforms. By automatically analyzing textual reviews and predicting ratings using deep learning models, the system reduces human bias and improves rating consistency.

The integration of sentiment analysis, automated rating generation, and real-time aggregation ensures scalability and reliability. The experimental results indicate that deep learning models such as LSTM and CNN provide high accuracy in sentiment classification tasks.

Overall, the system contributes to building a transparent and trustworthy online marketplace, helping customers make informed purchasing decisions. Future improvements may include transformer-based models and advanced fake review detection techniques to further enhance performance.

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