**AI E-COMMERCE BASED PRODUCT RATING SYSTEM**

# ABSTRACT

The system for grading products is an advanced approach designed to tackle the difficulties faced by customers when making selections about what to buy in the world of online shopping. In the current e-commerce era, customers mostly rely on product reviews and ratings to learn more about the features and performance of different products. The accuracy and applicability of these reviews, however, can differ greatly. The system uses deep learning and complex data analytics to thoroughly assess and compile user-generated information in order to get around these problems. Sentiment analysis, a potent tool that aids in determining the emotional tone of evaluations, is the feature that is employed. The satisfaction levels of customers who have written reviews are usefully shown by this analysis. Consumers can add another level of complexity to their decision-making process by evaluating the sentiment indicated in reviews, which helps them evaluate the overall sentiment and quality assessment of the products they are considering.

# 

# CHAPTER 1

# INTRODUCTION

Product rating systems have undergone a remarkable technological journey in the digital age, influencing consumers' ability to make well-informed purchasing decisions. Online retail platforms implemented primitive rating and review systems in the early days of e- commerce, when the World Wide Web was still in its infancy. These systems allowed users to leave text-based comments and assign simple star ratings. Even though they were ground breaking at the time, these early systems lacked sophisticated analytics and intricate algorithms that are now essential to contemporary product rating systems.

User-generated content and social media platforms started to become increasingly important in shaping consumer behavior as the internet grew. Customer experiences and opinions could be shared in online forums and on specialized review websites. At the same time, social media sites like Facebook and Twitter allowed users to share their product-related stories with a larger audience, which increased the impact of user-generated content.

Due to the increasing amount of user-generated content, online review aggregators and consumer feedback analytics tools began to appear in the mid-2000s. These platforms gathered and examined reviews from multiple sources in an effort to simplify the deluge of information. By using data analytics, they were able to identify patterns in customer sentiment and glean insightful information from reviews, facilitating consumers' evaluation of the general caliber of goods and services. When machine learning and sophisticated data analytics were integrated in the late 2000s and early 2010s, product rating systems underwent a true transformation. In order to evaluate the reviews' relevance to particular products, analyze the emotional tone of the reviews through sentiment analysis, and determine the veracity of the reviewers, machine learning algorithms were created.

These cutting-edge technologies significantly increased the reliability and accuracy of product reviews and ratings, providing consumers with a more trustworthy source of data to aid in their decision-making. Product rating systems nowadays have developed into complex technological ecosystems. They include elements like machine learning models that determine

the reliability of reviewers, data mining to extract insightful information from reviews, and natural language processing (NLP) for sentiment analysis. In addition to changing the way consumers make decisions about what to buy, these platforms have also had an impact on businesses, who now understand the importance of positive ratings and reviews for sales and brand reputation.

# 1.1Background History

The remarkable evolution of the product rating system can be attributed to the progress made in digital technology and the internet. E-commerce was in its infancy back in the early days of the World Wide Web. Customers could now give products stars and write text reviews thanks to the introduction of simple rating and review systems by online retailers like Amazon and eBay in the late 1990s and early 2000s. These early systems lacked the complex algorithms and analytics that we see today and were rather simple systems.

The next big technological development was the spread of social media and platforms for user-generated content. Customers could voice their experiences and opinions about different products on websites and forums devoted to product reviews and discussions. These platforms developed into important informational resources for prospective customers as a result of the rise in user-generated content. User-generated content's impact was further amplified by social media sites like Facebook and Twitter.

Product rating systems have become increasingly sophisticated since the late 2000s and early 2010s with the introduction of machine learning, deep learning, and advanced data analytics. Algorithms were created to measure the reliability of reviewers, analyze sentiment, and determine how relevant a review is to a particular product. This improved the ratings and reviews' accuracy and reliability. In order to address integrity concerns, machine learning was also used to enable automated detection of fraudulent reviews and review manipulation.

Product rating systems, which include a variety of technological components, are an essential component of the modern e-commerce landscape. These include machine learning models that can evaluate the reliability of reviewers and automatically filter out irrelevant or fraudulent content; natural language processing (NLP) for sentiment analysis; and data mining for gleaning insightful information from reviews. Systems for managing reputation and trust have also been incorporated to preserve the integrity of review sites.

# 1.2 Problem Statement

Product rating systems have become essential tools for consumers looking for trustworthy guidance when making purchases in the quickly growing digital marketplace. These systems' efficacy is, however, compromised by a number of serious issues. First, the frequency of falsified and altered reviews undermines customer confidence by casting doubt on the reliability of the ratings. Second, consumers may find it challenging to draw conclusions from product reviews that are meaningful due to a lack of established review criteria and an abundance of unstructured user-generated content. Third, there may be discrepancies between user expectations and product performance because product rating systems frequently are unable to take into consideration the changing needs and preferences of consumers. In order to guarantee that product rating systems keep giving customers useful, reliable, and pertinent information— and ultimately improve their online shopping experience—it is imperative that these issues are resolved.

# 1.3 Application of Product Rating System:

Product rating systems enhanced by deep learning have found diverse applications across various industries and domains. Here are some notable applications:

1. **E-commerce and Retail:** Deep learning-powered product rating systems are extensively used in e-commerce platforms like Amazon, Walmart, and eBay to analyze user reviews and ratings. These systems can automatically identify fake reviews, assess product sentiment, and provide more accurate aggregate ratings, helping consumers make informed purchasing decisions.
2. **Restaurant and Food Services:** Apps like Yelp and Zomato employ deep learning to process user reviews and ratings for restaurants and food establishments. This technology enables sentiment analysis, extracting valuable insights from user feedback to improve restaurant recommendations and ratings.
3. **Movie and Entertainment Industry**: Platforms like Rotten Tomatoes and IMDb use deep learning to evaluate user and critic reviews for movies, TV shows, and video games. This helps in aggregating review scores and providing more accurate recommendations to viewers and gamers.
4. **Hospitality and Travel:** Travel websites such as TripAdvisor leverage deep learning to analyze user reviews for hotels, vacation rentals, and travel destinations. These systems help in ranking accommodations and destinations based on user sentiments and preferences.
5. **Healthcare and Medical Products:**Deep learning-powered product rating systems are employed to evaluate and categorize user feedback on healthcare products, drugs, and medical services. These systems help patients and healthcare professionals make well-informed decisions regarding medical treatments and products.
6. **Automotive Industry:** Automotive websites like Edmunds and Kelley Blue Book use deep learning to assess user reviews and ratings for cars and vehicles. This information is valuable for potential buyers in their decision-making process.
7. **Consumer Electronics:** Product rating systems with deep learning are widely used in the evaluation of smartphones, laptops, and other consumer electronics. These systems help consumers assess product quality, durability, and performance based on user feedback.
8. **Real Estate and Housing:** Real estate platforms apply deep learning to analyze user reviews and ratings for real estate agents, property listings, and rental services. This technology assists prospective renters and buyers in making housing-related decisions.
9. **Educational Resources:** Online educational platforms use deep learning-based rating systems to evaluate and rank courses, textbooks, and educational materials. These systems offer students and educators valuable insights into the quality and effectiveness of educational resources.
10. **Travel Booking and Tourism:** Travel booking websites employ deep learning to assess user reviews for travel experiences, including tours, activities, and travel packages. This technology aids in recommending and ranking travel options.

# 1.4 Scope of the Project

The "AI E-Commerce based product rating system" project has a lot of potential to grow into a cutting-edge and extremely valuable application. The goal of this system is to use streamlit to overcome the shortcomings of current product rating systems. This project's scope covers a number of topics, such as data collection, preprocessing, model creation, and application across multiple domains. The primary focus of the scope is the gathering of a varied dataset of product reviews and ratings from a range of sources, including review platforms for restaurants and e-commerce websites. Using methods like natural language processing (NLP) to clean, organize, and convert unstructured text data into a format that is appropriate for deep learning makes data preprocessing an essential stage.

The creation of streamlit models is the project's central focus. This entails building neural networks, possibly with transformer-based models such as BERT or neural network architectures like recurrent neural networks (RNNs). These models will be trained to handle the fundamental problems with product rating systems, including sentiment analysis, review relevance evaluation, and credibility assessment.

The creation of an intuitive user interface that allows users to access and engage with the improved rating system is also included in the project's scope. Features like product comparisons, review summaries, and aggregated ratings will be available on this interface. These features will be powered by the deep learning model, giving users a smooth and educational experience.

# 1.5 Existing System

The existing system of our project's current system depends on Support Vector Machines (SVM) and Latent Dirichlet Allocation (LDA) to function. Textual user reviews are subjected to the extraction of topics and themes using Latent Domain Analysis (LDA), a topic modeling technique. It offers a methodical framework for deciphering the underlying trends in the reviews, making it possible to find recurring themes that could have an impact on product ratings. Rating prediction and sentiment analysis are two applications that use SVM. Strong machine learning models called support vector machines are excellent at identifying the positive, negative, or neutral sentiment of text.

# Limitations of the existing system:

**Lack of Review Credibility Assessment:** The system is susceptible to phony reviews and possible manipulation because it lacks mechanisms to evaluate the credibility of reviewers.

**Incapacity to Spot Review Manipulation:** It is devoid of sophisticated fraud detection methods to spot review bombing, phony reviews, and other types of manipulation that skew sentiment analysis and ultimate ratings.

**Time Sensitivity:** It's possible that the system won't take into account changes in user sentiment over time. The system might not be able to record changes in sentiment over time as product experiences change, which can be important for dynamic goods or services.

**Limited Review Relevance:** The accuracy of the sentiment analysis and rating predictions may be impacted by the inability of the current system to properly filter out irrelevant or off-topic reviews.

**Handling Multimodal Data Can Be Difficult:** Since it mainly uses textual data, it can't include other user-generated content types like images, videos, and audio that can offer important context and sentiment cues.

**Scalability:** When dealing with high review volumes, the performance of the current system may suffer, making it more difficult for it to deliver timely insights for products that have a lot of user feedback.

**Lack of Real-time Updates:** Users may be forced to rely on out-of-date information if the system does not provide real-time updates on ratings and reviews.

**Limited Adaptability to Diverse Domains:** Systems based on LDA and SVM may not be easily adjusted to different industries and domains, necessitating significant modifications for every application.

**Difficult Model Tuning:** SVM model fine-tuning can be difficult and time- consuming, requiring a lot of work to optimize model parameters for precise sentiment analysis.

**Difficulty Handling Polysemous Words:** Words with multiple meanings, or polysemous words, can be difficult for LDA and SVM to handle, which can cause mis-interpretations in sentiment analysis.

# 1.6 Proposed System

In the rapidly evolving landscape of e-commerce, the integration of advanced AI systems is paramount to enhance user experience and provide personalized recommendations. Creating an AI-based product rating system for an e-commerce platform using Streamlit involves several steps. Streamlit is a powerful Python library that simplifies the process of creating web applications with interactive and dynamic user interfaces. A comprehensive AI-based product rating system is proposed to leverage user reviews, sentiments, and collaborative and content-based filtering techniques. The proposed AI-based e-commerce product rating system utilizes advanced algorithms and machine learning techniques to revolutionize the conventional rating process. Key features include:

**Personalized Recommendations**: The system analyzes user behavior, preferences, and historical data to generate tailored product recommendations, enhancing user satisfaction and engagement.

**Sentiment Analysis**: Implementing natural language processing (NLP), the system evaluates user reviews to extract sentiments and provide a nuanced understanding of product feedback, leading to more accurate ratings.

**Dynamic Rating Adjustments**: Continuous learning from user interactions allows the system to dynamically adjust product ratings based on real-time trends and user feedback, ensuring relevance and reliability.

**Fraud Detection**: Employing anomaly detection algorithms, the system identifies and filters out fraudulent or biased reviews, maintaining the integrity of the rating system.

**User-Friendly Integration**: Seamlessly integrated into e-commerce platforms, the system offers an intuitive interface, making it easy for users to access and benefit from the enhanced product rating features.

Overall, this proposed system aims to elevate the e-commerce experience by providing users with personalized, trustworthy, and up-to-date product ratings, fostering increased consumer confidence and informed decision-making.

# CHAPTER 2

**LITERATURE SURVEY**

# S. M. Mohammad, ‘‘Sentiment analysis: Detecting valence, emotions, and other affectual states from text,’’ in Emotion Measurement. Sawston, U.K.: Woodhead, 2016

With an emphasis on obtaining and comprehending emotions and affective states from textual data, S. M. Mohammad's paper, "Sentiment Analysis: Detecting Valence, Emotions, and Other Affectual States from Text," which was included in the book "Emotion Measurement," explores the field of sentiment analysis. This paper offers a thorough examination of various approaches and strategies for locating sentiment, valence, and emotional cues in written material.

# S. Tao and H.-S. Kim, ‘‘Online customer reviews: Insights from the coffee shops

**industry and the moderating effect of business types,’’ Tourism Rev., vol. 77, no. 5, pp. 1349–1364, Aug. 2022.**

The study "Online Customer Reviews: Insights from the Coffee Shops Industry and the Moderating Effect of Business Types," written by S. Tao and H.-S. Kim and published in the "Tourism Review" in August 2022, explores the realm of online customer reviews in relation to the coffee shop industry. This study goes beyond traditional analysis of online reviews by looking at how various kinds of coffee shop enterprises are affected by and react to consumer feedback. The goal of the paper is to provide insightful information about the dynamic relationship between online customer reviews and the coffee shop industry by examining the moderating effects of different business types. The study probably offers a more nuanced understanding of how coffee shops handle and profit from online customer feedback, regardless of how big or small they are. Such studies play a crucial role in helping coffee shops and other service-oriented industries make the most of online reviews to improve overall performance and customer satisfaction.

# P. Dash, J. Mishra, and S. Dara, ‘‘Sentiment analysis on social network data and its marketing strategies: A review,’’ ECS Trans., vol. 107, Apr. 2022

Sentiment analysis as it relates to social network data is thoroughly reviewed in the paper "Sentiment Analysis on Social Network Data and its Marketing Strategies: A Review," written by P. Dash, J. Mishra, and S. Dara and published in the "ECS Transactions" in April 2022. The many approaches and techniques for analyzing sentiment in the context of social media and online networking are examined in this study. It probably goes into how sentiment analysis, which offers insights into consumer preferences, opinions, and trends, can help guide marketing strategies.

The study is an invaluable tool for researchers, companies, and marketers who want to better understand how to use the wealth of data found in social network data to improve their marketing strategies and establish stronger connections with their target markets. This review advances our knowledge of the mutually beneficial relationship that exists in the digital age between sentiment analysis and marketing strategies..

# S. Gupta and R. Sandhane, ‘‘Use of sentiment analysis in social media campaign design and analysis,’’ Cardiometry, vol. 22, pp. 351–363, May 2022

The use of sentiment analysis in social media campaign design and analysis is covered in the paper "Use of Sentiment Analysis in Social Media Campaign Design and Analysis," written by S. Gupta and R. Sandhane and published in "Cardiometry" in May 2022. This study probably looks at sentiment analysis's importance as a key instrument for planning, carrying out, and assessing social media campaigns. The study most likely looks into how sentiment analysis can help with comprehending and utilizing the feelings, thoughts, and emotions of the public on social media platforms to guide more adaptable and successful marketing campaigns. With the help of sentiment analysis, marketers and other professionals can better optimize their social media campaigns and make more data-driven, customer-focused, and successful digital marketing efforts. This work offers insightful information in this regard. The study adds to the expanding corpus of research on sentiment analysis's integration into the ever-changing field of social media marketing.

# J. Liu, S. Zheng, G. Xu, and M. Lin, ‘‘Cross-domain sentiment aware word embeddings for review sentiment analysis,’’ Int. J. Mach. Learn. Cybern., vol. 12, no. 2, pp. 343–354, Feb. 2021.

A advanced area of sentiment analysis is covered in the paper "Cross-domain Sentiment Aware Word Embeddings for Review Sentiment Analysis," written by J. Liu, S. Zheng, G. Xu, and M. Lin and published in the "International Journal of Machine Learning and Cybernetics" in February 2021. It is likely that this research explores the creation of word embeddings intended to capture sentiment in various domains. Stated differently, it delves into the fundamental challenge in natural language processing: teaching word embeddings to recognize and convey sentiment in textual data across a range of contexts.The goal of the paper is to improve review sentiment analysis, which is a crucial component of comprehending user opinions in a variety of domains, by improving machines' ability to understand and apply sentiment-aware word embeddings. In the end, this work benefits applications ranging from customer reviews to market research and beyond by offering creative ways to better capture and interpret sentiment across various domains. It also contributes to the ongoing evolution of sentiment analysis techniques.

# CHAPTER 3

**REQUIREMENT SPECIFICATIONS**

# 3.1 Software Requirements

# Operating System : Windows 10 and above

# Simulator tool : Visual Studio code

# Programming : Python

# 3.2 Hardware Requirements

# Processor : Any Intel or AMD x84-64 process

# RAM : Minimum 4GB and recommended 8GB

# Hard disk : 24GB to accommodate the project files, datasets and software tools

# Input device : Standard Keyboard and Mouse

# Output device : Standard Monitor

**3.3 System Tools**

Visual Studio Code is a fast and efficient source code editor available for Windows, Mac OSS X, and Linux on your PC. Together with a strong ecosystem of extensions for additional languages and runtimes (such as C++, C#, Java, Python, PHP, Go, and.NET), it comes with built-in support for JavaScript, TypeScript, and Node.js. Using the Electron Framework, Microsoft created the source code editor Visual Studio Code, or VS Code, for Windows, Linux, and macOS. Embedded Git, snippets, intelligent code completion, debugging support, and syntax highlighting are a few of the features. The AI e-commerce based product rating system relies on a set of sophisticated tools and technologies to function efficiently. Some key system tools include:

**Machine Learning Frameworks**: TensorFlow or PyTorch for developing and training machine learning models that analyze user behavior and generate personalized recommendations.

**Natural Language Processing (NLP) Libraries**: NLTK (Natural Language Toolkit) or spaCy for sentiment analysis on user reviews, extracting meaningful insights from textual data.

**Recommender System Libraries**: Collaborative filtering or content-based recommendation libraries like Surprise or LightFM to enhance personalized product recommendations.

**Data Storage and Processing**: Databases such as MongoDB, MySQL, or PostgreSQL for storing and managing user data, reviews, and product information. Apache Spark for distributed data processing, handling large-scale datasets efficiently.

**Web Development Frameworks**: Django or Flask for building the web application interface, integrating the AI-driven product rating system seamlessly into the e-commerce platform.

**Cloud Computing Services**: AWS, Google Cloud, or Azure for scalable and reliable hosting, storage, and computing resources.

**Frontend Technologies**: HTML, CSS, and JavaScript along with frameworks like React or Vue.js for creating a user-friendly and responsive interface.

**Continuous Integration/Continuous Deployment (CI/CD) Tools**: Jenkins, GitLab CI, or GitHub Actions to automate the testing and deployment processes, ensuring the system's stability and reliability.

**Anomaly Detection Tools**: Anomaly detection algorithms and libraries, such as Isolation Forest or One-Class SVM, to identify and filter out fraudulent or biased reviews.

**Monitoring and Logging Tools**: Tools like Prometheus or ELK stack (Elasticsearch, Logstash, Kibana) for monitoring system performance, logging, and troubleshooting. Combining these tools enables the development and operation of a robust AI e-commerce product rating system, delivering accurate and personalized recommendations to users.

**CHAPTER 4**

**METHODOLOGY**

**4.1 Working of the Proposed System**

The suggested system improves the analysis of user-generated content, such as product reviews, by utilizing Long Short-Term Memory (LSTM) algorithms in the product rating system. The LSTM is a kind of recurrent neural network (RNN) that is especially useful for processing textual information that changes over time because it can recognize and interpret sequential dependencies in data. Regarding the product rating scheme, LSTM operates as follows:

A series of words or tokens from a product review are first ingested by LSTM, which takes into account their appearance in both context and order. This makes it possible for LSTM to understand the innate temporal patterns in language as well as the development of concepts or emotions over the course of a review. In contrast to conventional sentiment analysis methods, which view text as a collection of words, LSTM recognizes that word order matters because context can alter how a statement is understood.

With every word it comes across, LSTM generates a hidden state as it processes the review. By combining data from earlier words with the current word, this dynamic hidden state allows the model to remember what it has already seen. Understanding intricate sentence structures and the nuanced expressions frequently found in product reviews depends heavily on this memory function.

The LSTM model learns the relationships between words and sentiments over time by being trained on a large dataset of product reviews with known sentiment labels. The model modifies its internal parameters during training in order to improve its ability to forecast the sentiment found in the reviews it reads.

The LSTM model can analyze fresh, unread product reviews after it has been trained. By analyzing the word order and taking the context into account, it interprets the tone and emotional cues in the text. As a result, sentiment analysis is more precise and context-aware, allowing the system to offer a more complex understanding of user preferences and opinions. Then, the sentiment and rating scores from various reviews can be combined by the LSTM- enhanced product rating system to provide a thorough evaluation of a product's quality and user satisfaction. Through the use of LSTM, the system delves into linguistic nuances and transcends basic sentiment analysis, enhancing the precision and breadth of insights it offers to users, companies, and online platforms. As a result, the user experience is improved overall, and better informed decision-making is enabled in the digital marketplace.

# 4.2 Sentiment Analysis :

One essential part of the product rating system is sentiment analysis, which is a potent natural language processing method with great importance in the online marketplace. It makes it possible for the system to examine the qualitative aspects of user-generated content, especially product reviews, in addition to the conventional quantitative ratings. Through a thorough analysis of the sentiment, feelings, and opinions expressed in text data, this process offers important insights into how consumers view and use goods and services.

Sentiment analysis is essentially the process of classifying text as expressing neutral, positive, or negative sentiment. Modern sentiment analysis techniques, on the other hand, are far more advanced and can identify emotions, capture nuanced sentiment expressions, and provide deeper context analysis. A product rating system needs this depth of analysis in order to give users a more comprehensive and detailed understanding of the performance, quality, and satisfaction of the product.

Machine learning algorithms and a variety of natural language processing techniques are used in sentiment analysis. These methods analyze reviews, extract pertinent data, and evaluate the text's emotional content. The ability to recognize words that convey emotion, comprehend sentence structures, and analyze context to discern irony, sarcasm, or conflicting emotions are important components. The sentiment analysis process is more accurate and reliable overall thanks to this multifaceted approach.

Sentiment analysis is very helpful to the product rating system because it makes it possible to extract insights from user reviews at a scale that would be difficult to accomplish manually. It improves the system's capacity to spot patterns, pinpoint typical problems, and pinpoint areas where particular products shine. Furthermore, sentiment analysis supports

transparency and trust in the digital marketplace by assisting the system in addressing issues such as manipulated and fraudulent reviews.

Sentiment analysis is essentially the foundation of the product rating system; it helps consumers make better decisions and provides businesses and online platforms with insightful data about customer feedback. The product rating system is elevated by the fusion of cutting-edge sentiment analysis methods with cutting-edge technologies, like deep learning with LSTM. This gives businesses a competitive edge in the constantly changing digital landscape and offers users a sophisticated and reliable resource.

# 4.3 LSTM Algorithm (Long Short-Term Memory) :

The Long Short-Term Memory (LSTM) algorithm plays a pivotal role in the product rating system, offering an advanced and nuanced approach to analyzing user-generated content, particularly product reviews. Unlike traditional sentiment analysis techniques, LSTM excels at understanding the temporal dependencies in language, making it highly effective in capturing the evolving sentiments expressed in reviews.

In real life, LSTM begins by reading through a product review's text and parsing each word, taking into account its placement in the text and its context. This essential distinction recognizes that words in a sentence are not isolated but rather interconnected, with context and order having a significant impact on meaning. Because of its ability to comprehend language in a sequential fashion, LSTM is able to comprehend the intricate sentence structures and nuanced expressions that are typical of product reviews.

While LSTM analyzes the review, it keeps track of words it has already encountered and merges that information with the word it is currently using to create an evolving hidden state. The model's memory is represented by this dynamic hidden state, which helps it remember context throughout the review. This memory function is especially helpful when handling user- generated content, which can vary greatly in length and complexity. It is essential to comprehending the development of ideas and sentiments in a review.

After being trained, the LSTM model can examine fresh, unpublished product reviews. It assesses the word order by taking into account each word's context and relationship to the overall sentiment expressed in the review. This leads to a more precise, context-aware sentiment analysis that surpasses simple positive/negative categorization, allowing the system to offer a deeper comprehension of user preferences and opinions.

LSTM improves the overall sentiment analysis process for the product rating system, making it possible for the system to more efficiently compile and interpret sentiment and rating scores from numerous reviews. This leads to a more thorough and perceptive evaluation of a product's quality and customer satisfaction. Through the use of LSTM, the product rating system goes beyond simple sentiment analysis, exploring the nuances of language and enhancing the breadth and precision of the insights it offers to customers, companies, and online platforms. In the end, this improves the user experience and enables better informed decision-making in the online market.

**4.4Streamlit**

Streamlit is an open-source Python library that allows you to create web applications for data science and machine learning with minimal effort. It simplifies the process of turning data scripts into shareable web apps. Streamlit is designed to be easy to use and requires minimal code to create interactive and visually appealing applications.

Here are some key features and aspects of Streamlit:

**Simplicity**: Streamlit is known for its simplicity. With just a few lines of code, you can create a web app. It is particularly well-suited for data scientists and analysts who want to quickly prototype and share their work.

**Rapid Prototyping**: Streamlit enables rapid prototyping by providing widgets (e.g., sliders, buttons, text inputs) that can be easily added to your Python script to create interactive elements.

**Wide Range of Widgets**: Streamlit comes with a variety of widgets that you can use to gather user input or display information, including sliders, buttons, text inputs, and charts.

**Data Integration**: You can easily integrate data visualizations created with popular plotting libraries like Matplotlib, Plotly, and Altair into your Streamlit app.

**Support for Machine Learning**: Streamlit is often used in conjunction with machine learning libraries. You can build interactive dashboards to showcase your machine learning models or results.

**Live Reloading**: Streamlit supports automatic reloading, so any changes you make to your script are immediately reflected in the app. This feature is helpful during the development process.

**Deployment Options**: Streamlit apps can be deployed on various platforms, including Streamlit Sharing (for free), Heroku, AWS, and others.

**Community and Extensions**: Streamlit has a growing community, and there are extensions and additional tools that can be used to enhance its functionality.

# 4.5 Home Page

# 4.6 Product Page

# 4.7 Review Page

# 4.8 Rating using Sentiment

# CHAPTER 5

**RESULT AND DISCUSSION**

# 5.1 Output of the proposed system:

# .

# CHAPTER 6

**CONCLUSION**

In conclusion, an AI-based product rating system in E-commerce holds significant promise and potential for enhancing the overall shopping experience for both consumers and businesses. The integration of artificial intelligence into the rating and review processes brings about several advantages.

Firstly, AI algorithms can analyze vast amounts of data efficiently and effectively, providing more accurate and unbiased product ratings. This not only helps consumers make informed purchasing decisions but also contributes to building trust and credibility within the E-commerce platform.

Moreover, AI-driven recommendation systems can personalize product suggestions based on individual preferences and behavior, leading to a more personalized and engaging shopping experience. This level of customization can contribute to increased customer satisfaction and loyalty.

Additionally, by automating the identification and filtering of fake or manipulated reviews, AI helps maintain the integrity of the rating system. This ensures that consumers receive reliable and authentic information, fostering a transparent and trustworthy online marketplace.

However, it is crucial to address potential challenges, such as ethical considerations, data privacy concerns, and the risk of algorithmic bias. Striking the right balance between automation and human oversight is essential to maintain a fair and inclusive product rating system. In summary, the system for rating products is a crucial part of the online marketplace that benefits companies and customers alike. Its capabilities have been enhanced over time by sophisticated methods like sentiment analysis and, more recently, deep learning models like LSTM.

The product rating system offers customers a trustworthy information source to help them make wise purchasing decisions. It enhances the shopping experience by providing thorough insights into product quality and user satisfaction.

Companies get access to real-time customer feedback through the system, which helps them with strategy, product development, and marketing. Additionally, by preventing review manipulation, it improves transparency and trust.

Sentiment analysis gains a new dimension with the integration of deep learning, especially LSTM, which helps to overcome adaptability issues and linguistic complexities. This development could completely transform the system by providing more precise and contextually relevant reviews and ratings.

The system for rating products will probably keep changing in the future to accommodate the ever-changing digital environment. It will continue to be an important tool, encouraging trust, transparency, and well-informed decision-making in the online marketplace, by embracing cutting-edge technologies and data-driven insights.