Regression Analysis Based Pricing Recommendations for E-commerce Retailers

A Project Report submitted
in partial fulfillment of the requirements
for the award of the degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE & ENGINEERING

By

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2024 – 2025

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

CERTIFICATE

*This is to certify that the project entitled "**Regression analysis based pricing Recommendations for E-Commerce Retailers**", is being submitted by **B.Jahnavi, G.Durga Anvitha, G.Harshitha, G.S.S.Spoorthi, B.Karuna Priya** bearing the **Regd.No's. 21B01A0517, 21B01A0548, 21B01A0550, 21B01A0556,22B05A0502** respectively in partial fulfillment of the requirements for the award of the degree of "**Bachelor of Technology** in **Computer Science & Engineering**" is a record of bonafide work carried out by them under my guidance and supervision during the academic year 2024– 2025 and it has been found worthy of acceptance according to the requirements of the university.*

Internal Guide **Head of the Department**

External Examiner

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ABSTRACT

Under the era of e-commerce, pricing strategies are of utmost importance to achieve optimal profits with customer satisfaction. In this study, we introduce a data-driven framework for price recommendation and product examination through machine learning and web scraping methods.

We collect product information from various online stores, preprocess them, and apply a Random Forest Regression model to forecast optimum selling prices. Moreover, we utilize fuzzy string matching for enhancing the accuracy of product identification. Our research shows that intelligent price suggestions can help greatly ineffective competitive price planning for companies with a balance between profitability and demand in the marketplace.

Experimental outcomes show that the recommended system yields reliable price suggestions while ensuring a minimum profit margin of 20%. This study makes contributions to the development of AI-based pricing models in the e-commerce and retail analytics domain. Index Terms—E-commerce, Artificial Intelligence, Machine Learning, Price Optimization, Competitor Analysis, Regression Models, Random Forest, Gradient Boosting, Decision Trees, APIs, Web Scraping.

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INTRODUCTION

The rise of e-commerce has drastically transformed the global retail ecosystem, creating a highly competitive landscape where pricing plays a pivotal role in consumer decision-making and overall business profitability. With millions of products being sold across platforms like Flipkart, Amazon, Reliance Digital, and Croma, sellers must navigate complex pricing dynamics to remain viable. In this highly saturated digital marketplace, setting the right price is no longer just a matter of cost-plus strategy—it's a data-driven challenge that requires real-time insights and intelligent automation.

For large-scale e-commerce giants, dynamic pricing strategies powered by artificial intelligence (AI) and machine learning (ML) have become the norm. These systems dynamically adjust prices based on competitor activity, inventory levels, seasonal trends, and consumer behaviour. However, smaller retailers and individual sellers often lack access to such advanced tools, resulting in pricing strategies that are either static or overly reliant on manual research and guesswork. These approaches are time-consuming, error-prone, and frequently misaligned with real-time market conditions, leading to revenue loss and missed opportunities.

This research presents a comprehensive machine learning-based framework that empowers e-commerce retailers to generate intelligent pricing recommendations using regression analysis. The system integrates data collection via web scraping, preprocessing techniques, fuzzy string matching for product alignment, and the application of Random Forest Regression to predict optimal selling prices. By automating the pricing process, our solution allows sellers to maintain competitive edge and profitability while minimizing manual effort.

Web scraping enables the extraction of real-time product data—such as price, reviews, and ratings—from top Indian e-commerce platforms. This data serves as the foundation for predictive modelling. Product titles often vary slightly across platforms, so we employ fuzzy string matching techniques to accurately identify and align equivalent items, ensuring valid price comparisons. Once aligned, the system leverages historical pricing trends and market features to forecast recommended prices that meet a defined profit margin threshold.

Dynamic pricing, once exclusive to major retailers, can now be made accessible to smaller businesses through this lightweight yet powerful tool. For instance, companies like Amazon continuously optimize pricing using machine learning to maximize conversions and maintain market dominance. Our system emulates a similar strategy on a more approachable scale, delivering actionable recommendations without requiring deep technical expertise.

By bridging the gap between data science and e-commerce operations, this research contributes significantly to the field of AI-driven retail analytics. It not only enhances pricing accuracy but also improves customer satisfaction by offering competitively priced products. As the digital marketplace continues to evolve, the demand for such intelligent pricing solutions will only increase. The proposed model addresses this need by offering a scalable, accurate, and efficient approach to price optimization for retailers of all size

2. SYSTEM ANALYSIS

System analysis serves as a crucial phase in the development lifecycle, acting as the compass that guides the transformation from the existing state to the proposed enhanced system. This section encompasses a detailed exploration of the existing system, an in-depth presentation of the proposed system, and a thorough feasibility study, all tailored to the context of our project, "Regression analysis based Pricing Recommendations for E-commerce Retailers."

2.1 Existing System

Builds a **machine learning model that can predict the price of e-commerce products** based on certain product features. This helps sellers estimate an appropriate selling price for their items.

1. Data Collection:

- The project uses a sample dataset from **Flipkart** named flipkart_com-ecommerce_sample.csv.
- The dataset includes product details such as:
    a. Product Name
    b. Brand
    c. Product Category Tree
    d. Retail Price
    e. Discounted Price
    f. Rating

2. Data Preprocessing:

To prepare the data for model training, several preprocessing steps are performed:

- **Handling missing values**: Any blank or incomplete entries are either removed or filled.
- **Encoding categorical data**: Since machine learning models work with numbers, text fields like "brand" or "category" are converted to numerical values using **Label Encoding**.
- **Cleaning columns**: Unnecessary columns like URLs or long text fields are dropped.
- **Converting prices to float**: All price values are cleaned and converted into usable numerical formats.

3. Model Training:

- The model used is **Linear Regression**, which is a basic algorithm for price prediction.

• The dataset is split into **training and testing sets**, so the model can be trained on one part and evaluated on another.
• After training, the model learns the relationship between features like rating, brand, and category to predict product price.

4. Prediction & Evaluation:

• Once trained, the model can predict the **discounted price** of a product when provided with its other features.
• The model's accuracy is measured using:

1. **R² Score** – Indicates how well the model explains the price variations.
2. **MAE and MSE** – Measure the difference between predicted and actual prices.

• The final output shows the predicted price of a product when certain features are input.
• The result is printed on the console (no GUI).

2.2 Proposed System

The proposed system for ”Regression Analysis Based Pricing Recommendations for E-commerce Retailers” is a comprehensive, data-driven solution designed to optimize product pricing strategies. It begins by automating the collection of product information—including titles, prices, ratings, and reviews—from major e-commerce platforms such as Flipkart, Reliance Digital, and Croma using web scraping techniques. The collected data is then preprocessed through cleaning, normalization, and feature engineering, which transforms raw data into structured inputs suitable for analysis.

A Random Forest Regression model is employed to predict optimal selling prices by analyzing historical pricing trends, competitive market data, and customer feedback, while fuzzy string matching ensures accurate alignment of products across different platforms. The system further provides interactive visualizations for price comparison, empowering retailers to make informed, competitive pricing decisions that guarantee a minimum profit margin.

This approach not only streamlines the pricing process but also lays the foundation for future enhancements, such as real-time price tracking and the integration of additional market indicators, making it a valuable tool in the dynamic e-commerce landscape. The whole system has the following components:

1. **Data collection:**

Product data (titles, prices, ratings, reviews) is scraped from Flipkart, Reliance Digital, and Croma using Selenium and BeautifulSoup to handle dynamic and static content Historical sales and pricing data for the model training need to be collected too.

2. **Data preprocessing:**

Collected data is cleaned by handling missing values and outliers, converting prices to numeric format, and normalizing numerical features to prepare for analysis.

3. **Feature Engineering:**

Spotting the price line over time and in the past.

4. **Price Analysis and Visualization :**

Visualizations such as price distribution charts and ratings versus price graphs are generated to compare product pricing trends across the different platforms.

5. **Price Recommendation Using Machine Learning :**

A Random Forest Regression model is trained on features like ratings and prices to predict an optimal selling price that ensures a minimum profit margin.

6. **Evaluation and Reporting:**

Model performance is evaluated using metrics like Mean Absolute Error and R^2, and comprehensive reports are generated to summarize accuracy and effectiveness of the pricing strategy.

2.3 Feasibility Study

A thorough feasibility study ensures the proposed price recommendation system is practical, sustainable, and deployable in a real-world e-commerce environment. The study evaluates the system across three primary dimensions: technical, economic, and operational feasibility.

1. Technical Feasibility:

The system is highly feasible from a technical standpoint, as it leverages widely adopted technologies and tools:

• **Technology Stack:** The project uses Python along with libraries such as Scikit-learn, Pandas, NumPy, Selenium, BeautifulSoup, and FuzzyWuzzy. These are all open-source, community-supported, and well-documented, making development and debugging straightforward.

• **Machine Learning Integration:** Random Forest Regression is used due to its robustness and ability to handle high-dimensional, non-linear datasets efficiently without overfitting.

• **Web Scraping Compatibility**: E-commerce platforms like Flipkart, Reliance Digital, and Croma provide product data in a structured format, allowing seamless scraping using tools like Selenium.

• **System Requirements**: The application can be developed and run on a system with basic specifications such as an Intel i5 processor, 8GB RAM, and standard broadband internet, making it accessible even on mid-range personal computers.

• **Extendability**: The system is designed with modularity, allowing for easy integration of other platforms (like Amazon or TataCliq), APIs, or real-time tracking modules in the future.

2. Economic Feasibility:

The project is cost-effective and can be implemented with minimal financial investment:

• **Open Source Tools**: The use of free and open-source software drastically reduces licensing and development costs.

• **Cloud Deployment Options**: Platforms like Heroku, AWS Free Tier, or Streamlit Cloud can be used for hosting the web app without any significant upfront cost.

• **Resource Utilization**: The training and execution of models require minimal computational resources, especially for Random Forests, which can be run on CPUs without needing GPUs.

• **Long-Term ROI**: For small- to mid-sized online sellers, the system can significantly reduce manual effort, improve pricing accuracy, and enhance profitability, justifying any initial development effort.

3. Operational Feasibility

The system is practical to use and can be easily adopted by non-technical users:

• **User-Friendly Interface**: Built using Streamlit, the UI offers an intuitive experience for users to input product details and receive price recommendations and competitor insights.
• **Decision Support**: With features like dynamic price graphs, competitor price display, and confidence scoring for fuzzy matches, users receive actionable insights, not just predictions.
• **Maintenance and Monitoring**: Once deployed, the system can be maintained with minimal effort, with scraping scripts scheduled and machine learning models updated periodically.
• **Scalability**: The system architecture supports scaling, enabling expansion to include real-time data, sentiment analysis of reviews, or deep learning models for improved predictions.

4. Legal and Ethical Feasibility

• **Compliance**: Web scraping practices follow publicly available data and respect site terms of use. The system avoids scraping login-protected or copyrighted content.
• **Transparency and Control**: Users can view how recommendations are generated (e.g., cost margin, competitor data), fostering trust in automated suggestions.

3. SYSTEM REQUIREMENTS

3.1 Software Requirements

Programming Languages: Python (for data processing, machine learning), JavaScript (for frontend)

Frameworks/Libraries: TensorFlow/PyTorch (deep learning), Scikit-Learn (machine learning), NLTK/Spacy (NLP), Flask/Django (backend), React/Angular (frontend)

Database: MongoDB or PostgreSQL for storing price and review data

APIs: Web scraping or APIs for e-commerce platforms (if permitted), Notification APIs (email or SMS)

Operating System: Linux or Windows

Development Environment: VS Code or PyCharm

3.2 Hardware Requirements

Processor: Multi-core (Intel i5 or higher recommended) for running ML models effectively

Memory: Minimum 16 GB RAM for handling large datasets and faster processing

Storage: SSD with at least 512 GB capacity to store datasets and trained models

GPU (Optional): For faster training and processing of deep learning models

3.3 Functional Requirements

Competitor Price Monitoring:The system should track competitor prices across multiple e-commerce platforms and display real-time price updates for similar products.

Customer Review Collection and Sentiment Analysis: Collect and analyze customer reviews from various platforms using NLP to identify sentiment (positive, neutral, negative) for each product.

Feature-Based Sentiment Analysis: Identify and categorize sentiments based on specific product features (e.g., price, quality, design).

Price Recommendation Engine: Provide sellers with recommended price adjustments based on competitor pricing, market trends, and customer sentiment.

Market Trend and Demand Prediction: Predict product demand and pricing trends using historical data to guide inventory and marketing strategies.

Review Summarization: Summarize customer reviews to extract key insights, allowing sellers to understand customer preferences quickly.

Custom Alerts and Notifications: Notify sellers of significant competitor price changes or emerging review trends for real-time adjustments.

4. SYSTEM DESIGN

System design is a critical phase in the software development lifecycle where the conceptualization from earlier stages begins to take concrete form. It involves the creation of a detailed blueprint that outlines the architecture, components, modules, and interactions within the system. This phase not only guides the development team but also serves as a communication tool, ensuring a shared understanding of the system's structure and functionality among stakeholders.

4.1 Introduction to Software Design

Software design is a crucial phase in the development lifecycle, where user requirements are systematically translated into a structured framework that guides the implementation of the system. It involves defining system architecture, data processing workflows, user interactions, and functionality to ensure the final product meets the intended objectives efficiently. A well-structured software design enhances scalability, maintainability, and performance, ensuring that the system can adapt to future improvements and expansions.

In the context of our project, "*Regression analysis based pricing Recommendations for E-Commerce Retailers*," the software design phase is essential in building a seamless pricing optimization system. The design focuses on integrating web scraping, machine learning models, competitor price tracking, and sentiment analysis into a cohesive framework. This includes the development of data collection pipelines (using Selenium and BeautifulSoup), preprocessing mechanisms (handling missing values, feature extraction), machine learning models (Random Forest, XGBoost, Gradient Boosting for price prediction), and an interactive dashboard (built using Streamlit or Flask). The system must be designed for real-time data updates, allowing e-commerce sellers to dynamically adjust their prices based on market trends and customer insights.

Additionally, the software design considers the user experience, ensuring that the interface is simple yet powerful for sellers to input product details and receive optimized price recommendations. By focusing on scalability, efficiency, and automation, the design enables a high-performance, AI-driven pricing system that enhances competitive positioning in the e-commerce market.

Software Design in Our Project:

In our project, "*Regression analysis based pricing Recommendations for E-Commerce Retailers*," the software design phase plays a critical role in integrating multiple technologies and data-driven models. The system must effectively combine web scraping for data collection, natural language processing (NLP) for sentiment analysis, and machine learning algorithms for price prediction, ensuring a smooth and efficient workflow. The design must balance accuracy, scalability, and real-time data processing to deliver precise pricing recommendations for e-commerce sellers.

The system architecture follows a modular approach, ensuring that each component—data collection, preprocessing, machine learning models, and user interface—functions independently while seamlessly interacting with the overall system. The design defines data flow from web scraping (Selenium, BeautifulSoup) to data preprocessing (handling missing values, feature extraction) and predictive modeling (Random Forest, Gradient Boosting, and XGBoost for price optimization). The system must also specify communication pathways between the backend (price prediction models) and the frontend dashboard (built using Streamlit or Flask), ensuring smooth data exchange and visualization.

Furthermore, the design must address key challenges, such as handling real-time price fluctuations, improving sentiment analysis accuracy, and ensuring an intuitive user interface for decision-making. The system should be optimized for scalability and real-time processing, allowing sellers to adjust their pricing dynamically based on market trends. By focusing on efficiency, automation, and adaptability, the software design ensures that the price recommendation system provides accurate, data-driven insights that enhance e-commerce competitiveness.

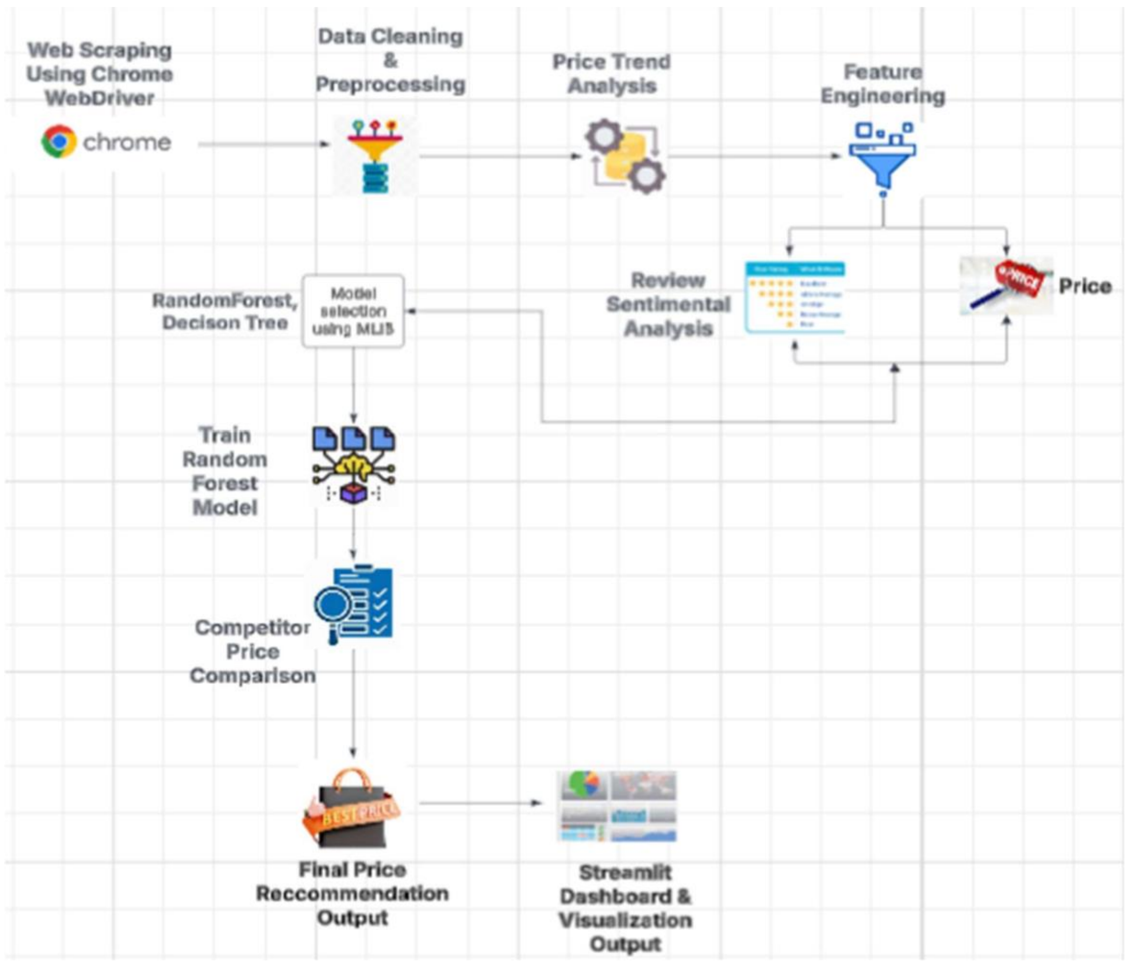

Web Scraping Using Chrome WebDriver
chrome
Data Cleaning & Preprocessing
Price Trend Analysis
Feature Engineering
Review Sentimental Analysis
Price
RandomForest, Decison Tree
Model selection using MLJS
Train Random Forest Model
Competitor Price Comparison
Final Price Reccommendation Output
Streamlit Dashboard & Visualization Output

Fig 4.1.1 System Design

4.2. UML Diagrams

Use-oriented techniques are widely used in software requirement analysis and design. Use cases and usage scenarios facilitate system understanding and provide a common language for communication. This paper presents a scenario-based modeling technique and discusses its applications. In this model, scenarios are organized hierarchically and they capture the system functionality at various abstraction levels including scenario groups, scenarios, and sub-scenarios.

Combining scenarios or sub-scenarios can form complex scenarios. Data are also separately identified, organized, and attached to scenarios. This scenario model can be used to cross check with the UML model. It can also direct systematic scenario-based testing including test case generation, test coverage analysis with respect to requirements, and functional regression testing.

An object contains both data and methods that control the data. The data represents the state of the object. A class describes an object and they also form a hierarchy to model the real-world system. The hierarchy is represented as inheritance and the classes can also be associated in different ways as per the requirement. Objects are the real-world entities that exist around us and the basic concepts such as abstraction, encapsulation, inheritance, and polymorphism all can be represented using UML.UML is powerful enough to represent all the concepts that exist in object-oriented analysis and design.

The Primary goals in the design of the UML are as follows:

- Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
- Provide extendibility and specialization mechanisms to extend the core concepts.
- Be independent of particular programming languages and development processes.
- Provide a formal basis for understanding the modeling language.
- Encourage the growth of the OO tools market.
- Support higher level development concepts such as collaborations, frameworks, patterns and components.
- Integrate best practice

Class diagram:

It depicts a static view of an application. It represents the types of objects residing in the system and the relationships between them.

In software engineering, a class diagram in the unified modeling language (uml) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.

A class consists of its objects, and also it may inherit from other classes.

A class diagram is used to visualize, describe, document various different aspects of the system, and also construct executable software code.

It shows the attributes, classes, functions, and relationships to give an overview of the software system. It constitutes class names, attributes, and functions in a separate compartment that helps in software development.

Since it is a collection of classes, interfaces, associations, collaborations, and constraints, it is termed as a structural diagram.

Class diagram contains

- Classes
- Interfaces
- Dependency, generalization and association

Class diagram is basically a graphical representation of the static view of the system and represents different aspects of the application. A collection of class diagrams represent the whole system.

The following points should be remembered while drawing a class diagram –

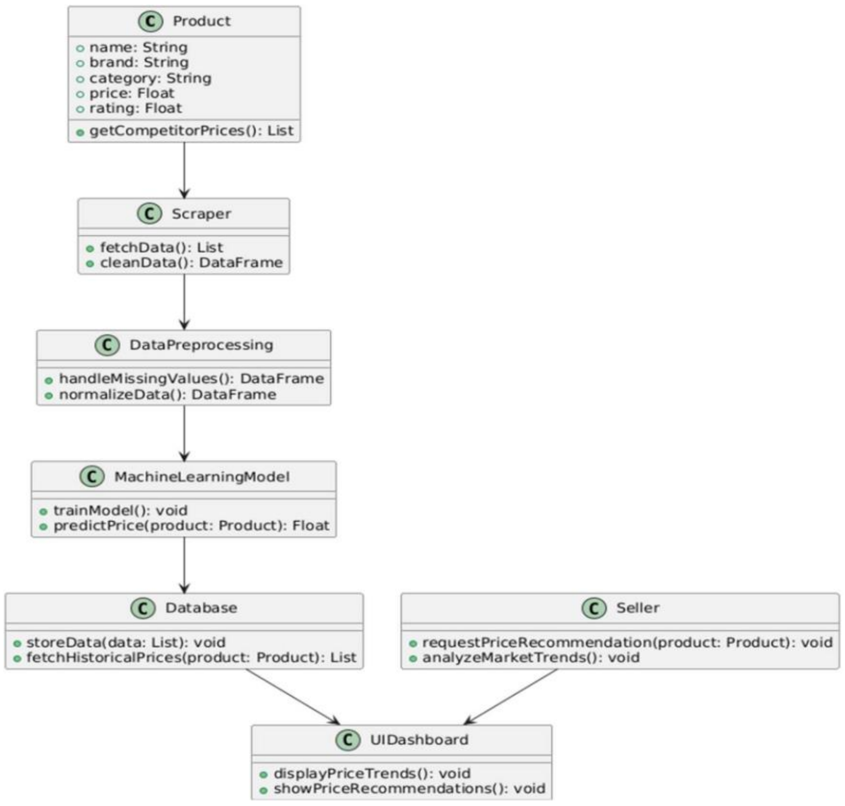
- The name of the class diagram should be meaningful to describe the aspect of the system.
- Each element and their relationships should be identified in advance.

• Responsibility (attributes and methods) of each class should be clearly identified

• For each class, a minimum number of properties should be specified, as unnecessary properties will make the diagram complicated.

• Use notes whenever required to describe some aspect of the diagram. At the end of the drawing it should be understandable to the developer/coder.

• Finally, before making the final version, the diagram should be drawn on plain paper and reworked as many times as possible to make it correct


Product
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brand: String
category: String
price: Float
rating: Float
getCompetitorPrices(): List
Scraper
fetchData(): List
cleanData(): DataFrame
DataPreprocessing
handleMissingValues(): DataFrame
normalizeData(): DataFrame
MachineLearningModel
trainModel(): void
predictPrice(product: Product): Float
Database
storeData(data: List): void
fetchHistoricalPrices(product: Product): List
Seller
requestPriceRecommendation(product: Product): void
analyzeMarketTrends(): void
UIDashboard
displayPriceTrends(): void
showPriceRecommendations(): void

Fig4.2.1 class Diagram Price Recommendation System

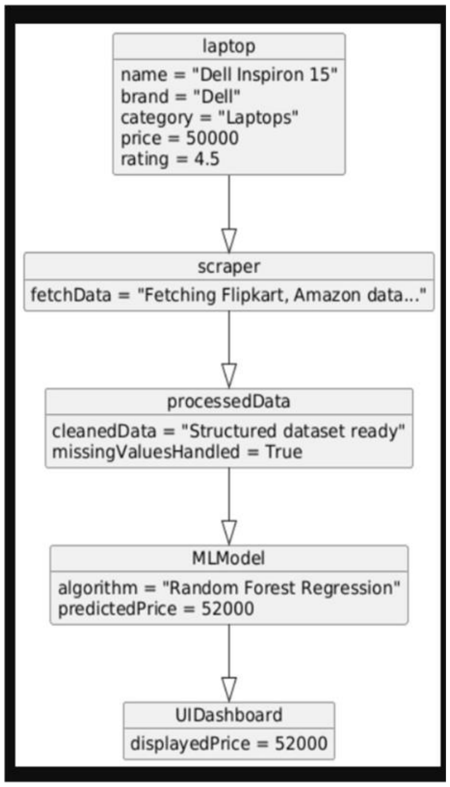
Object Diagram:

The object diagram visualizes the instances of classes in a system at a particular point in time. It provides a snapshot of how objects interact and are related during runtime.

- It involves objects, their attributes, and links.
- It represents the state of objects and their relationships at a specific moment.

- It helps in understanding the system's structure and the flow of data between instances.

Since it focuses on the real-time representation of objects, it is a concrete representation of a class diagram but with actual instances and values. The main purpose of an object diagram is to provide a clear understanding of how objects interact in a specific scenario, helping developers analyze system behavior in different conditions. It is useful for debugging, testing, and understanding object interactions in an application.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missingValuesHandled = True
MLModel
algorithm = "Random Forest Regression"
predictedPrice = 52000
UIDashboard
displayedPrice = 52000

Fig 4.2.2 Object Diagram for Price Recommendation System

Component diagram:

A component diagram is a type of structural diagram in the Unified Modeling Language (UML) that depicts the high-level components or modular parts of a system and their interactions. It provides a visual representation of the organization and relationships between components within a system or software application.

At its core, a component diagram consists of various components, each representing a distinct modular unit or building block of the system. These components encapsulate functionality and behavior, and they can be of different types, such as classes, modules, subsystems, or even entire software systems.

The connections between components are represented by lines, called connectors, which illustrate the dependencies and relationships between components. These relationships can include dependencies, associations, aggregations, or compositions, depending on the nature of the interaction between the components. For example, a dependency relationship might indicate that one component relies on the functionality provided by another component.

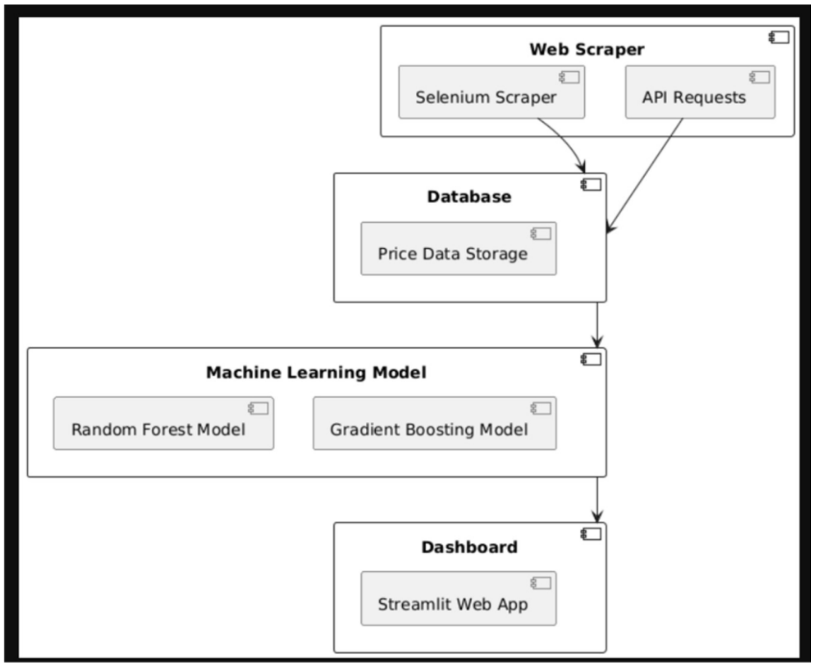


Fig 4.2.3. Component Diagram for Price Recommendation System

Deployment diagram:

The deployment diagram visualizes the physical hardware on which the software will be deployed. It portrays the static deployment view of a system.

- It involves the nodes and their relationships.
- It ascertains how software is deployed on the hardware.
- It maps the software architecture created in design to the physical system architecture, where the software will be executed as a node.

Since it involves many nodes, the relationship is shown by utilizing communication paths. The main purpose of the deployment diagram is to represent how software is installed on the hardware component. It depicts in what manner a software interacts with hardware to perform its execution.

Fig 4.2.3 Deployment Diagram for Price Recommendation System

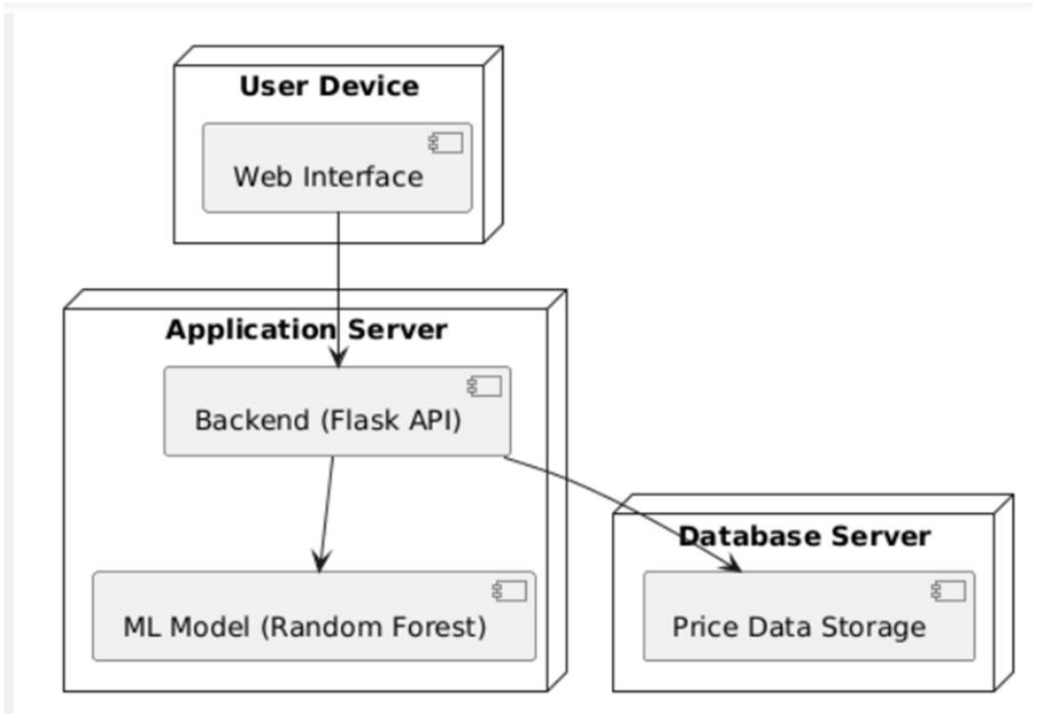


Fig 4.2.4 Deployment Diagram for Price Recommendation System

Use case diagram:

A use case diagram in the unified modeling language (uml) is a type of behavioral diagram defined by and created from a use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

Following are the purposes of a use case diagram given below:

- It depicts the external view of the system.
- It recognizes the internal as well as external factors that influence the system.
- It represents the interaction between the actors. Use case diagrams commonly contains
- Use cases
- Actors
- Dependency, generalization and association relationships.

Use cases : A use case is a software and system engineering term that describes how a user uses a system to accomplish a particular goal.

Actors : An actor is a person, organization or external system that plays a role in one more interactions with the system

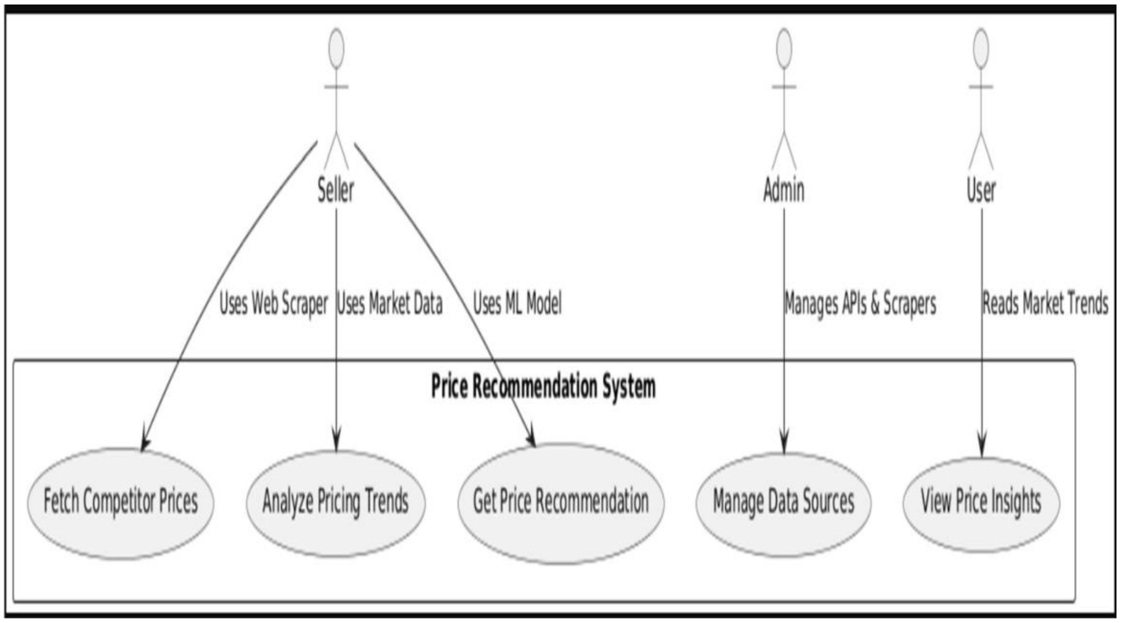


Fig 4.2.5 Use Case diagram for Price Recommendation System

Sequence Diagram:

The sequence diagram visualizes the interaction between different objects in a system in a time-ordered sequence. It portrays the dynamic behavior of a system by illustrating how processes interact with one another.

- It involves objects, messages, and lifelines.
- It captures the flow of messages exchanged between objects over time.
- It demonstrates the order in which operations occur and how objects collaborate to accomplish a task.

Since it emphasizes the time-based interaction of objects, relationships between them are represented using messages and activation bars. The main purpose of a sequence diagram is to show how different components of a system communicate and the sequence of interactions. It helps in understanding the system's workflow, process flow, and the order of method calls between objects.

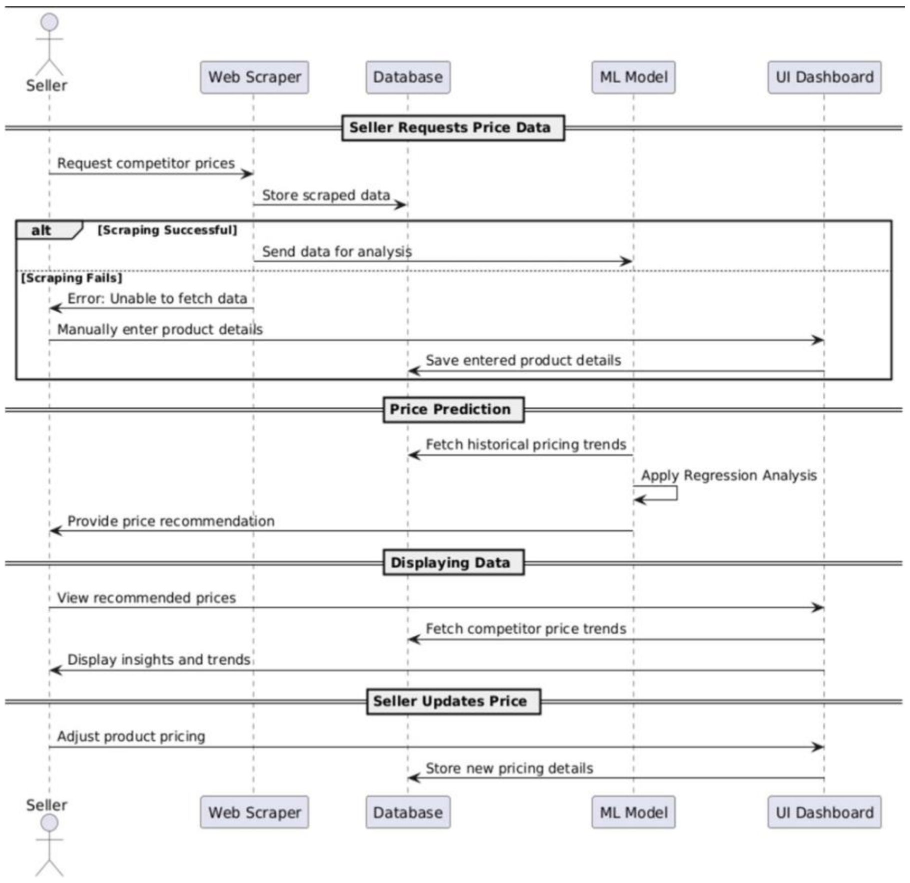

Seller
Web Scraper
Database
ML Model
UI Dashboard
Seller Requests Price Data
Request competitor prices
Store scraped data
alt
[Scraping Successful]
Send data for analysis
[Scraping Fails]
Error: Unable to fetch data
Manually enter product details
Save entered product details
Price Prediction
Fetch historical pricing trends
Apply Regression Analysis
Provide price recommendation
Displaying Data
View recommended prices
Fetch competitor price trends
Display insights and trends
Seller Updates Price
Adjust product pricing
Store new pricing details

Fig 4.2.6 Sequence Diagram for Price Recommendation System

Collaboration Diagram:

The collaboration diagram, also known as a communication diagram, visualizes the structural organization of objects that interact in a system. It portrays the dynamic interaction between objects based on the association and message flow.

- It involves objects, links, and messages.
- It emphasizes the relationship between objects and their interactions.

- It shows how different objects are connected and exchange messages to complete a process.

  Since it focuses on object relationships rather than the sequence of events, the interactions are represented through numbered messages along links. The primary purpose of a collaboration diagram is to illustrate how different components of a system work together to achieve a specific functionality. It helps in understanding the role of each object in communication and how they coordinate to achieve a task.

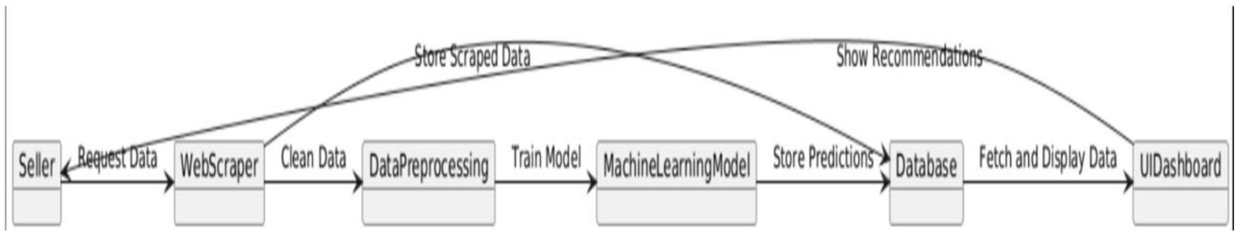


Fig 4.2.7 Collaboaration Diagram for Price Recommendation System

Activity Diagram:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the unified modeling language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system.

An activity diagram shows the overall flow of control. The activity diagram helps in envisioning the workflow from one activity to another. It puts emphasis on the condition of flow and the order in which it occurs.

The flow can be sequential, branched, or concurrent, and to deal with such kinds of flows, the activity diagram has come up with a fork, join, etc. Activity diagrams are mainly used as a flowchart that consists of activities performed by the system.

Activity diagrams are not exactly flowcharts as they have some additional capabilities. These additional capabilities include branching, parallel flow, swim lane, etc.

Before drawing an activity diagram, we must have a clear understanding about the elements used in the activity diagram.

The main element of an activity diagram is the activity itself. An activity is a function performed by the system. After identifying the activities, we need to understand how they are associated with constraints and conditions.

Before drawing an activity diagram, we should identify the following elements –

- Activities
- Association
- Conditions
- Constraints

Once the above-mentioned parameters are identified, we need to make a mental layout of the entire flow. This mental layout is then transformed into an activity diagram.

The basic usage of the activity diagram is similar to the other four UML diagrams.

The specific usage is to model the control flow from one activity to another. This control flow does not include messages.

Activity diagram is suitable for modeling the activity flow of the system. An application can have multiple systems.

Activity diagram also captures these systems and describes the flow from one system to another. This specific usage is not available in other diagrams.

These systems can be databases, external queues, or any other system. This diagram is used to model the activities which are nothing but business requirements. The diagram has more impact on business understanding rather than on implementation details.

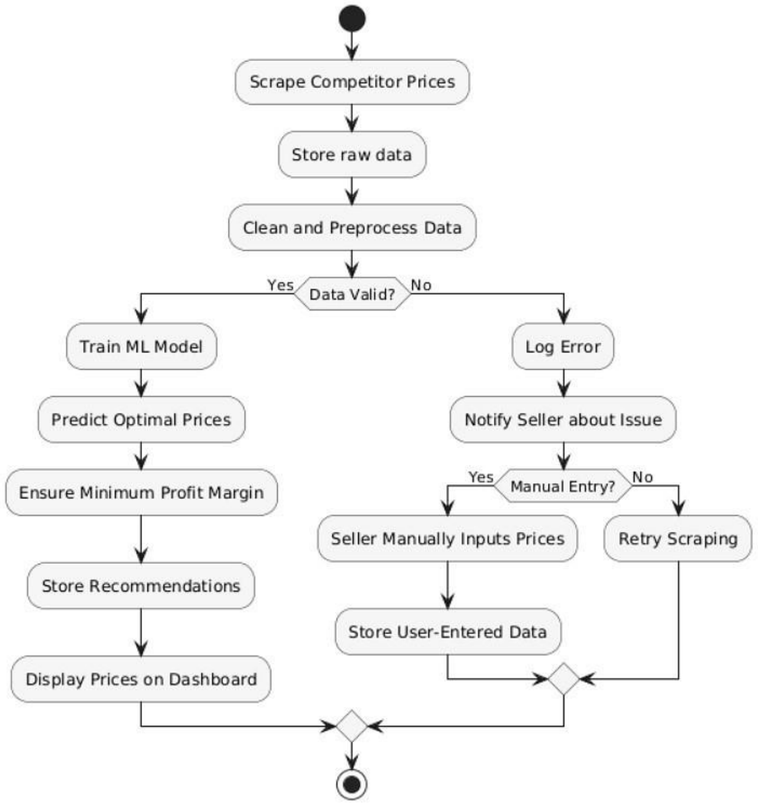


Fig 4.2.8 Activity Diagram for Price Recommendation System

5. System Implementation

5.1. Introduction to System Implementation

System implementation is a crucial phase in the software development life cycle where the designed specifications are converted into a fully functional system through coding and integration. This stage involves developing individual modules, integrating machine learning models, conducting initial testing, and optimizing the system to ensure it meets the intended functionality. The implementation phase serves as a bridge between theoretical design and a working application, making it a critical step before final testing and deployment.

Key Aspects of System Implementation

1. Coding and Programming

During this phase, developers write the actual code based on the system design. The implementation of the **Regression Analysis-Based Pricing Recommendations for E-Commerce Retailers** project involves:

- **Python** for data processing, machine learning, and web scraping.
- **Selenium** for extracting product prices and reviews from e-commerce platforms.
- **Pandas & NumPy** for data cleaning and preprocessing.
- **Scikit-learn/Randomforest** for regression-based price prediction.
- **Matplotlib & Seaborn** for data visualization and trend analysis.

2. Integration of Components

A well-structured integration process ensures that different modules function together seamlessly. The key integrations in this project include:

- **Web Scraping Module** – Extracts real-time pricing data from online retail platforms.
- **Data Cleaning & Preprocessing Module** – Structures and refines collected data.
- **Machine Learning Module** – Utilizes regression analysis to predict optimal pricing strategies.
- **Sentiment Analysis Module** – Evaluates product reviews to understand market trends.
- **Visualization Dashboard** – Displays competitor comparisons, price trends, and recommendations.

3. Testing

Testing is a fundamental part of implementation to ensure the system's accuracy and efficiency. The project undergoes:

- **Unit Testing** – Validating the correctness of individual components like web scraping, data preprocessing, and ML model predictions.
- **Integration Testing** – Ensuring that data flows correctly between modules and the dashboard displays accurate insights.
- **Regression Model Evaluation** – Assessing the accuracy of price predictions using **RMSE, MAE, and R^2 scores** to optimize performance.

4. Refinement and Optimization

Continuous improvements are made during implementation to enhance system efficiency. Optimization includes:

- **Enhancing Web Scraping Speed** – Implementing multi-threading and request handling to avoid bans.
- **Feature Selection for ML Models** – Choosing the most relevant features to improve regression accuracy.
- **Reducing Model Training Time** – Implementing data normalization and hyperparameter tuning for performance gains.
- **Improving Dashboard UI/UX** – Optimizing visual elements for a seamless user experience.

5. Documentation

Comprehensive documentation is created to provide clear insights into the system architecture, algorithms, and implementation methodologies. The documentation includes:

- **Codebase Explanation** – Organized and well-commented code for future scalability.
- **Algorithm Workflow** – Flowcharts and explanations for the machine learning model.
- **User Guide** – Instructions for utilizing the dashboard and interpreting predictions.

System implementation marks a crucial milestone in our project, where well-structured design specifications are transformed into a functional system through coding and development. This phase is essential in converting theoretical concepts into a practical solution, empowering **e-commerce retailers with data-driven pricing strategies**.

Translating Design into Code

At the core of this implementation phase is the development of Python-based scripts to integrate various components, including **web scraping, machine learning models, and an interactive dashboard**. The technologies used in this project include:

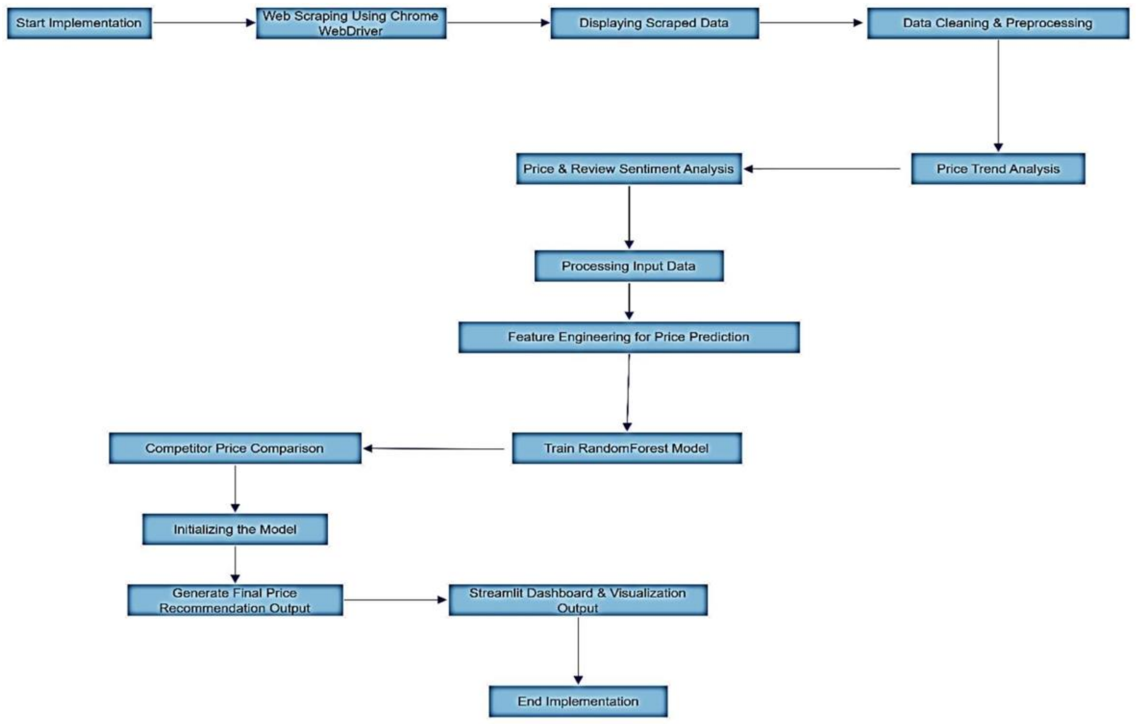

Start Implementation
Web Scraping Using Chrome WebDriver
Displaying Scraped Data
Data Cleaning & Preprocessing
Price Trend Analysis
Price & Review Sentiment Analysis
Processing Input Data
Feature Engineering for Price Prediction
Train RandomForest Model
Competitor Price Comparison
Initializing the Model
Generate Final Price Recommendation Output
Streamlit Dashboard & Visualization Output
End Implementation

Fig 5.1 implementation levels

• **Web Scraping with Chrome WebDriver** (Selenium) for dynamically extracting product prices and customer reviews from multiple e-commerce platforms.

• **Data Processing & Feature Engineering** (Pandas, NumPy) for cleaning, structuring, and extracting meaningful insights from scraped data.

• **Machine Learning with RandomForest** (Scikit-learn) for regression-based price prediction, leveraging historical pricing data and market trends.

• **Interactive Dashboard with Streamlit** for a **user-friendly, web-based interface** to display pricing recommendations and competitor analysis.

This phase requires expertise in **web automation, machine learning, and UI development** to ensure a seamless and efficient system.

Integration of Technological Components

A well-structured integration ensures smooth data flow between different modules. The key integration steps include:

- **Automating Web Scraping using Chrome WebDriver** – Extracting real-time competitor pricing data from multiple e-commerce platforms.
- **Processing and Structuring Data** – Cleaning and transforming raw data for use in the **RandomForest regression model**.
- **Training and Deploying RandomForest Model** – Using **ensemble learning** to improve the accuracy of price predictions.
- **Building a Streamlit Dashboard** – Providing **real-time pricing insights, competitor comparisons, and data visualizations** in an easy-to-use interface.

By integrating these technologies, the system delivers **actionable pricing recommendations for retailers** based on competitor analysis and historical trends.

Testing and Iterative Refinement

Testing is a **key phase** of implementation to ensure system reliability and accuracy. The following testing methods are applied:

- **Unit Testing** – Ensuring web scraping, data preprocessing, and model training function correctly.
- **Integration Testing** – Verifying that scraped data is accurately processed and fed into the **RandomForest model**.
- **Model Performance Evaluation** – Assessing **RMSE, MAE, and R^2 scores**, and fine-tuning hyperparameters to enhance prediction accuracy.
- **User Testing with Streamlit** – Collecting feedback on UI/UX to refine visualization and functionality for better usability.

An **iterative approach** ensures the system continuously improves based on testing results and user feedback.

Optimization for Real-World Usage

To ensure the system is **scalable and efficient**, several optimization strategies are implemented:

• **Enhancing Web Scraping Performance** – Optimizing Chrome WebDriver scripts to **reduce response time and avoid detection**.

• **Feature Selection for Model Optimization** – Selecting the most relevant **pricing-related features** to improve prediction accuracy.

• **Reducing Model Training Time** – Applying **hyperparameter tuning and parallel processing** for improved efficiency.

• **Improving Dashboard UI/UX** – Enhancing **visual elements and interactive filters** in Streamlit for better user experience.

Documentation for Sustainability

Comprehensive documentation is created to support future development, covering:

• **Codebase Explanation** – Organized documentation of scraping, preprocessing, and modeling scripts.

• **Algorithm Workflow** – Detailed descriptions of the **RandomForest regression model** and feature selection process.

• **User Guide** – Instructions for interacting with the **Streamlit dashboard** and interpreting price recommendations.

5.2 Project Modules

The project's architecture is divided into distinct modules, each serving a specific purpose in analyzing and predicting **optimal product prices for e-commerce retailers**. These modules work together to extract data, process it, apply machine learning techniques, and present insights via an interactive dashboard.

1. Web Scraping Module (Chrome WebDriver - Selenium)

The **Web Scraping Module** is responsible for extracting real-time product prices and customer reviews from **Flipkart, Reliance Digital, and Croma**. It uses **Chrome WebDriver with Selenium** to automate browsing, navigate product listings, and collect structured data.

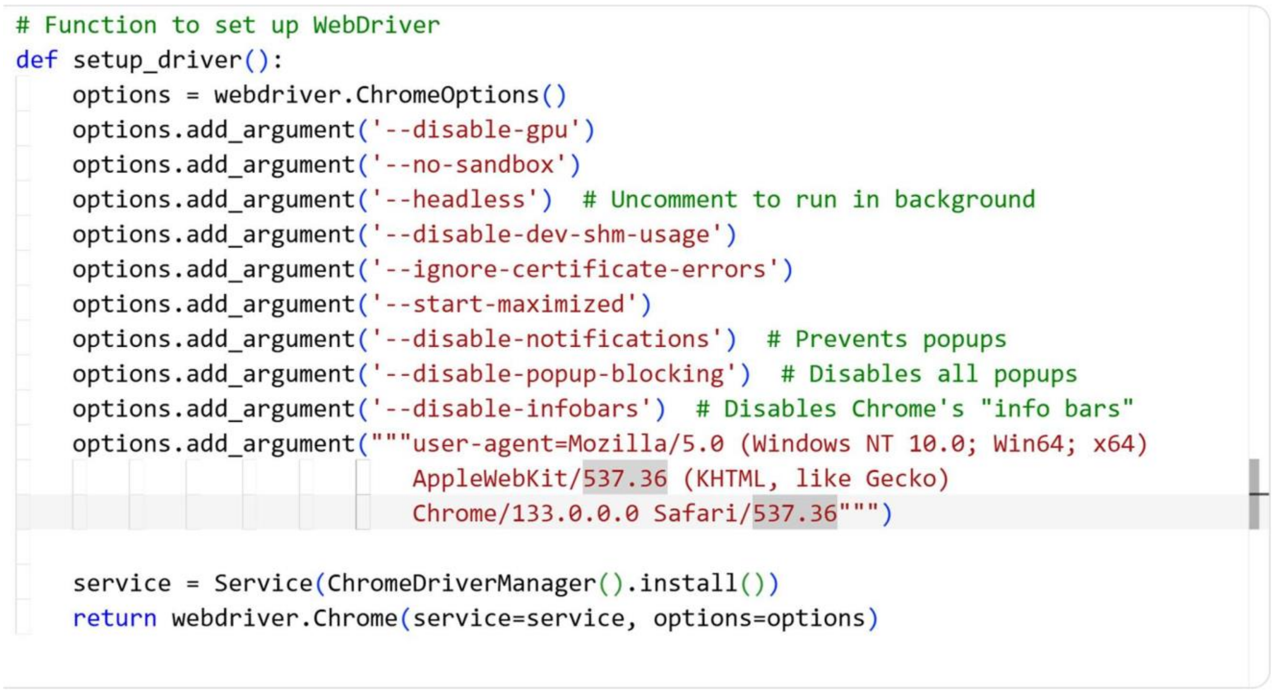
Key Features:

• **Automated data extraction** of product names, prices, and reviews.

• **Dynamic content handling** using Selenium to interact with AJAX-loaded elements.

• **Storage of scraped data** in CSV/Database for further analysis.

Output: A structured dataset containing product details, prices, and customer reviews.



```python
# Function to set up WebDriver
def setup_driver():
    options = webdriver.ChromeOptions()
    options.add_argument('--disable-gpu')
    options.add_argument('--no-sandbox')
    options.add_argument('--headless')  # Uncomment to run in background
    options.add_argument('--disable-dev-shm-usage')
    options.add_argument('--ignore-certificate-errors')
    options.add_argument('--start-maximized')
    options.add_argument('--disable-notifications')  # Prevents popups
    options.add_argument('--disable-popup-blocking')  # Disables all popups
    options.add_argument('--disable-infobars')  # Disables Chrome's "info bars"
    options.add_argument("""user-agent=Mozilla/5.0 (Windows NT 10.0; Win64; x64)
                         AppleWebKit/537.36 (KHTML, like Gecko)
                         Chrome/133.0.0.0 Safari/537.36""")

    service = Service(ChromeDriverManager().install())
    return webdriver.Chrome(service=service, options=options)
```

Fig 5.2.1 Web Scraping Implementation

2. Data Cleaning & Preprocessing Module

The **Data Cleaning Module** ensures that the scraped data is structured, free from inconsistencies, and ready for machine learning analysis.

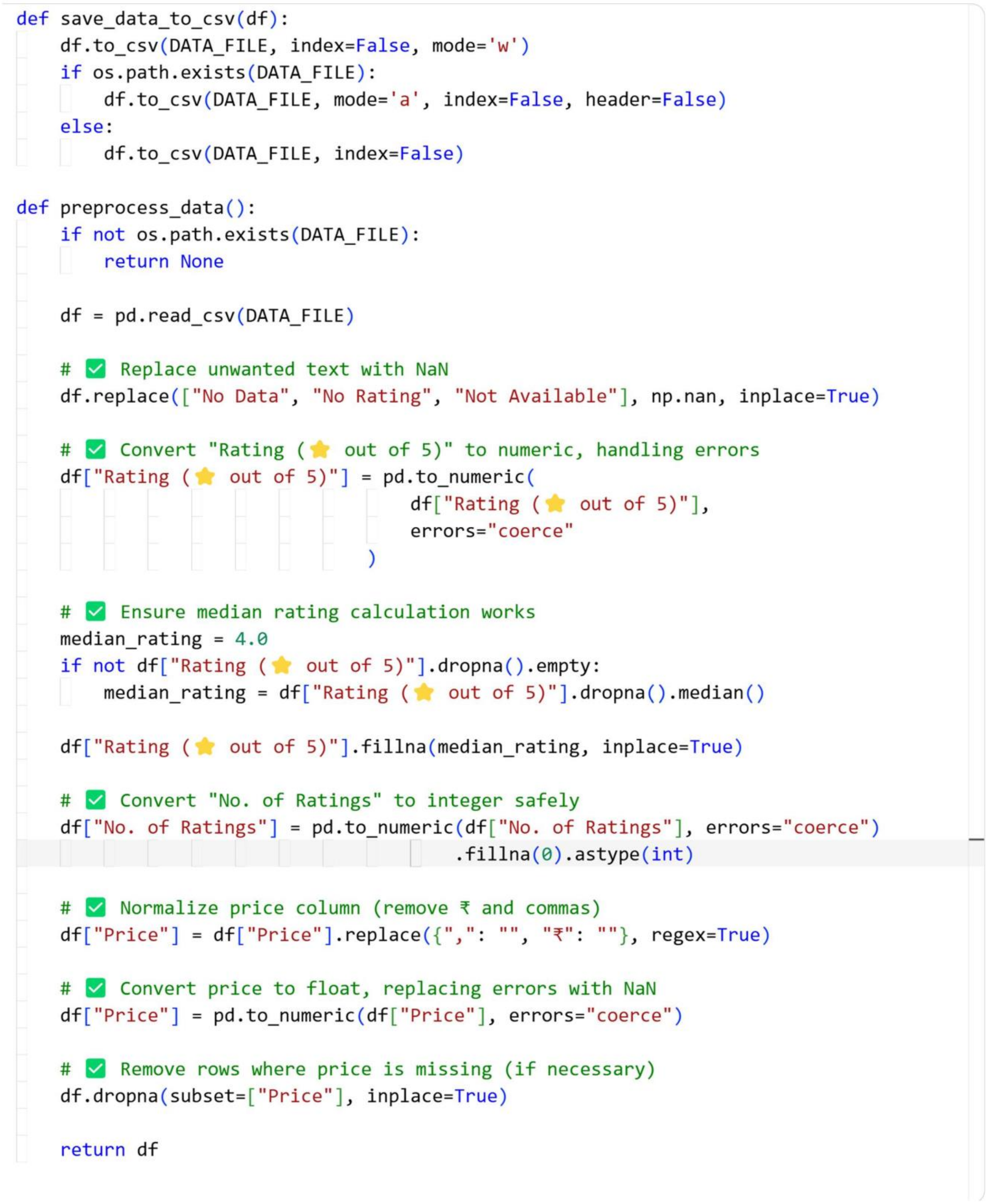
Key Features:

• **Handling missing values** by removing incomplete records or filling in missing fields.

• **Standardizing product names** to avoid duplicate entries from different platforms.

• **Filtering out irrelevant data**, such as promotional prices or unavailable products.

Output: A clean, structured dataset for price analysis.



```python
def save_data_to_csv(df):
    df.to_csv(DATA_FILE, index=False, mode='w')
    if os.path.exists(DATA_FILE):
        df.to_csv(DATA_FILE, mode='a', index=False, header=False)
    else:
        df.to_csv(DATA_FILE, index=False)

def preprocess_data():
    if not os.path.exists(DATA_FILE):
        return None

    df = pd.read_csv(DATA_FILE)

    # ✅ Replace unwanted text with NaN
    df.replace(["No Data", "No Rating", "Not Available"], np.nan, inplace=True)

    # ✅ Convert "Rating (⭐ out of 5)" to numeric, handling errors
    df["Rating (⭐ out of 5)"] = pd.to_numeric(
                                    df["Rating (⭐ out of 5)"],
                                    errors="coerce"
                                )

    # ✅ Ensure median rating calculation works
    median_rating = 4.0
    if not df["Rating (⭐ out of 5)"].dropna().empty:
        median_rating = df["Rating (⭐ out of 5)"].dropna().median()

    df["Rating (⭐ out of 5)"].fillna(median_rating, inplace=True)

    # ✅ Convert "No. of Ratings" to integer safely
    df["No. of Ratings"] = pd.to_numeric(df["No. of Ratings"], errors="coerce")
                                       .fillna(0).astype(int)

    # ✅ Normalize price column (remove ₹ and commas)
    df["Price"] = df["Price"].replace({",": "", "₹": ""}, regex=True)

    # ✅ Convert price to float, replacing errors with NaN
    df["Price"] = pd.to_numeric(df["Price"], errors="coerce")

    # ✅ Remove rows where price is missing (if necessary)
    df.dropna(subset=["Price"], inplace=True)

    return df
```

Fig 5.2.2 Data Cleaning and Preprocessing

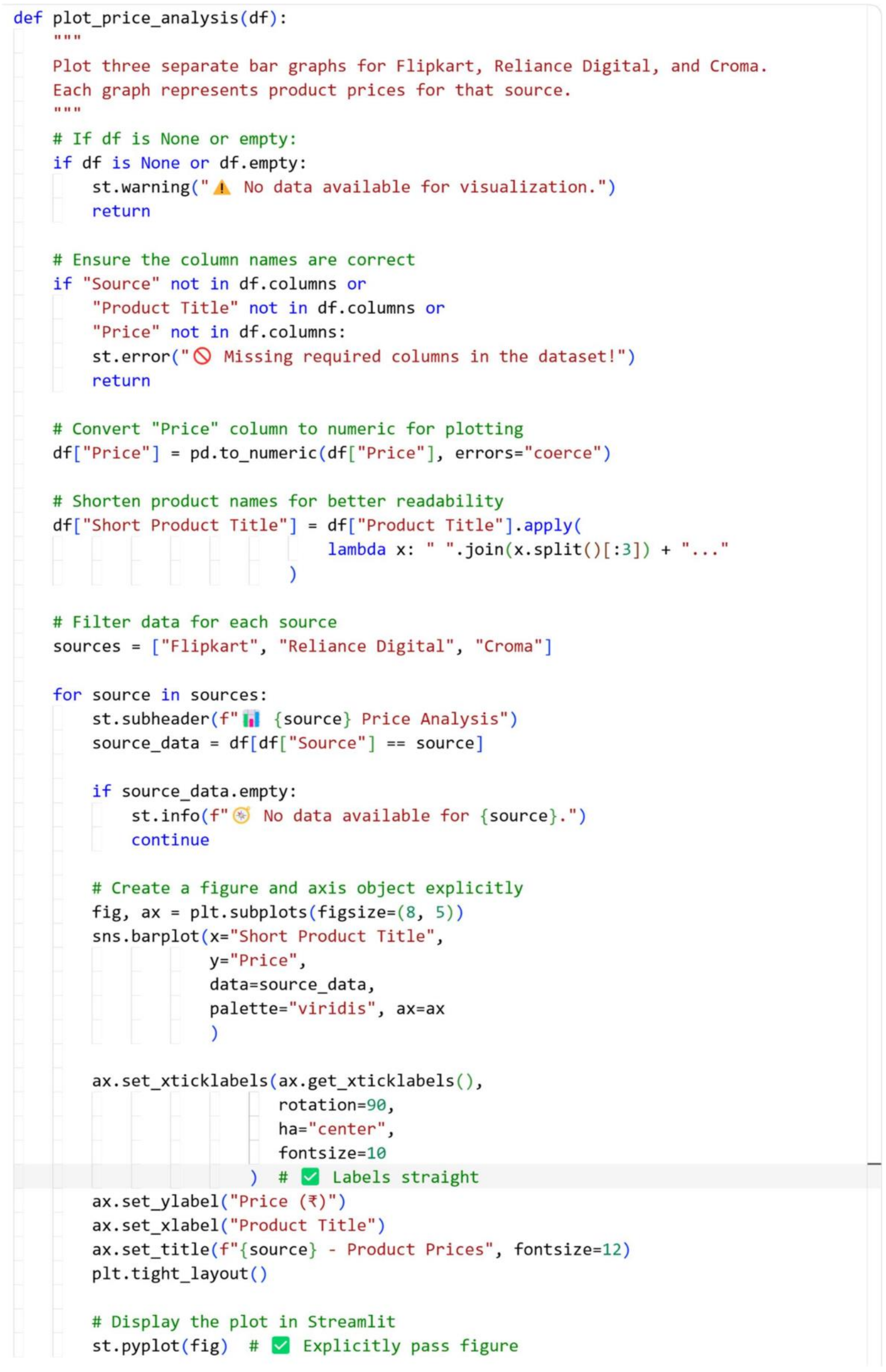
3. Price Trend Analysis Module

This module analyzes **historical price trends** to identify pricing patterns and fluctuations.

Key Features:

- **Analyzing price changes** over time for each product category.
- **Identifying seasonal trends**, discounts, and price variations across platforms.
- **Visualizing trends** using line charts and histograms.

Output: A detailed analysis of price trends across **Flipkart, Reliance Digital, and Croma**



```python
def plot_price_analysis(df):
    """
    Plot three separate bar graphs for Flipkart, Reliance Digital, and Croma.
    Each graph represents product prices for that source.
    """
    # If df is None or empty:
    if df is None or df.empty:
        st.warning("⚠️ No data available for visualization.")
        return

    # Ensure the column names are correct
    if "Source" not in df.columns or
        "Product Title" not in df.columns or
        "Price" not in df.columns:
        st.error("🚫 Missing required columns in the dataset!")
        return

    # Convert "Price" column to numeric for plotting
    df["Price"] = pd.to_numeric(df["Price"], errors="coerce")

    # Shorten product names for better readability
    df["Short Product Title"] = df["Product Title"].apply(
                                    lambda x: " ".join(x.split()[:3]) + "..."
                                )

    # Filter data for each source
    sources = ["Flipkart", "Reliance Digital", "Croma"]

    for source in sources:
        st.subheader(f"📊 {source} Price Analysis")
        source_data = df[df["Source"] == source]

        if source_data.empty:
            st.info(f"🧭 No data available for {source}.")
            continue

        # Create a figure and axis object explicitly
        fig, ax = plt.subplots(figsize=(8, 5))
        sns.barplot(x="Short Product Title",
                    y="Price",
                    data=source_data,
                    palette="viridis", ax=ax
                    )

        ax.set_xticklabels(ax.get_xticklabels(),
                           rotation=90,
                           ha="center",
                           fontsize=10
                           ) # ✅ Labels straight
        ax.set_ylabel("Price (₹)")
        ax.set_xlabel("Product Title")
        ax.set_title(f"{source} - Product Prices", fontsize=12)
        plt.tight_layout()

        # Display the plot in Streamlit
        st.pyplot(fig)  # ✅ Explicitly pass figure
```

Fig 5.2.3 Price Trend Analysis

4. Price & Review Sentiment Analysis Module

This module applies **Natural Language Processing (NLP)** to analyze customer reviews and their impact on product pricing.

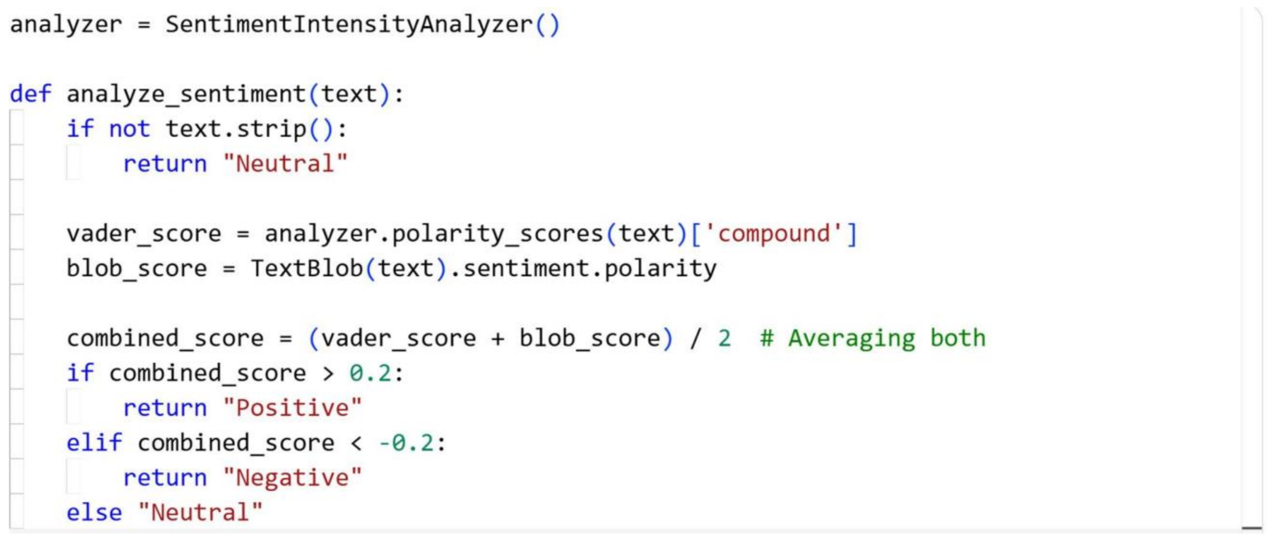
Key Features:

• **Sentiment classification** (Positive, Neutral, Negative) using NLP techniques.

• **Review-based insights** to determine how customer feedback correlates with pricing.

• **Text preprocessing** (removing stopwords, lemmatization, tokenization).

Output: A sentiment-based pricing insight, helping sellers understand how reviews influence price changes.



```
analyzer = SentimentIntensityAnalyzer()

def analyze_sentiment(text):
    if not text.strip():
        return "Neutral"

    vader_score = analyzer.polarity_scores(text)['compound']
    blob_score = TextBlob(text).sentiment.polarity

    combined_score = (vader_score + blob_score) / 2  # Averaging both
    if combined_score > 0.2:
        return "Positive"
    elif combined_score < -0.2:
        return "Negative"
    else "Neutral"
```

Fig 5.2.4 Price and Review Sentiment Analysis

5. Feature Engineering for Price Prediction

This module selects and transforms relevant data features to **improve the accuracy of price predictions**.

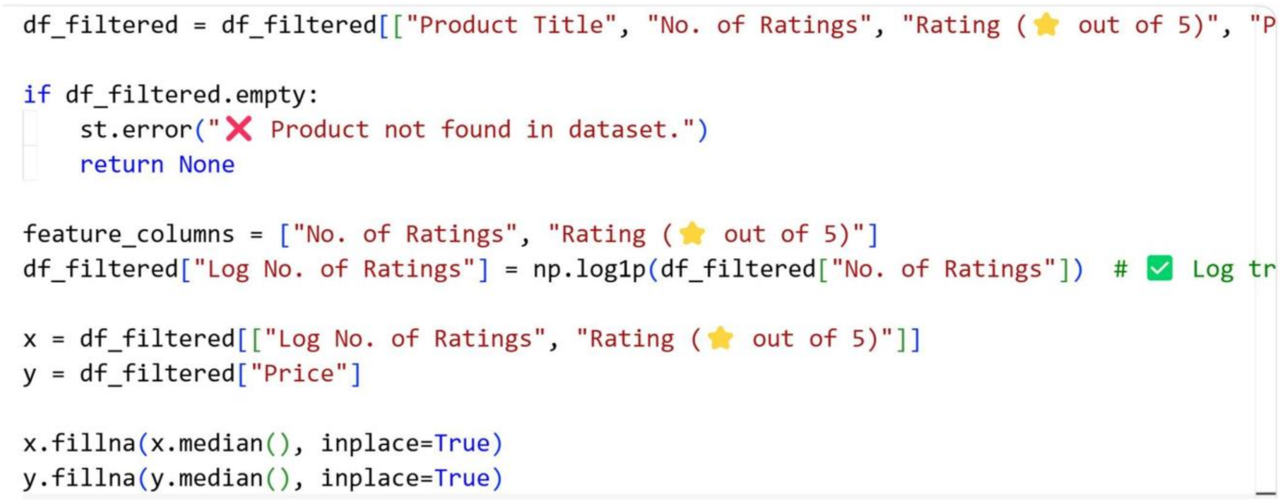
Key Features:

• **Identifying key attributes**, such as brand, product specifications, and historical prices.

• **Scaling numerical features** to normalize price values.

• **Encoding categorical variables** (e.g., product type, brand) for model training.

Output: A well-structured dataset optimized for machine learning.



```
df_filtered = df_filtered[["Product Title", "No. of Ratings", "Rating (⭐ out of 5)", "P

if df_filtered.empty:
    st.error("❌ Product not found in dataset.")
    return None

feature_columns = ["No. of Ratings", "Rating (⭐ out of 5)"]
df_filtered["Log No. of Ratings"] = np.log1p(df_filtered["No. of Ratings"])  # ✅ Log tr

x = df_filtered[["Log No. of Ratings", "Rating (⭐ out of 5)"]]
y = df_filtered["Price"]

x.fillna(x.median(), inplace=True)
y.fillna(y.median(), inplace=True)
```

Fig 5.2.5 Feature Engineering for Price Prediction

6. Machine Learning Model - RandomForest for Price Prediction

The **Machine Learning Module** utilizes the **RandomForest Regression Model** to predict optimal pricing.

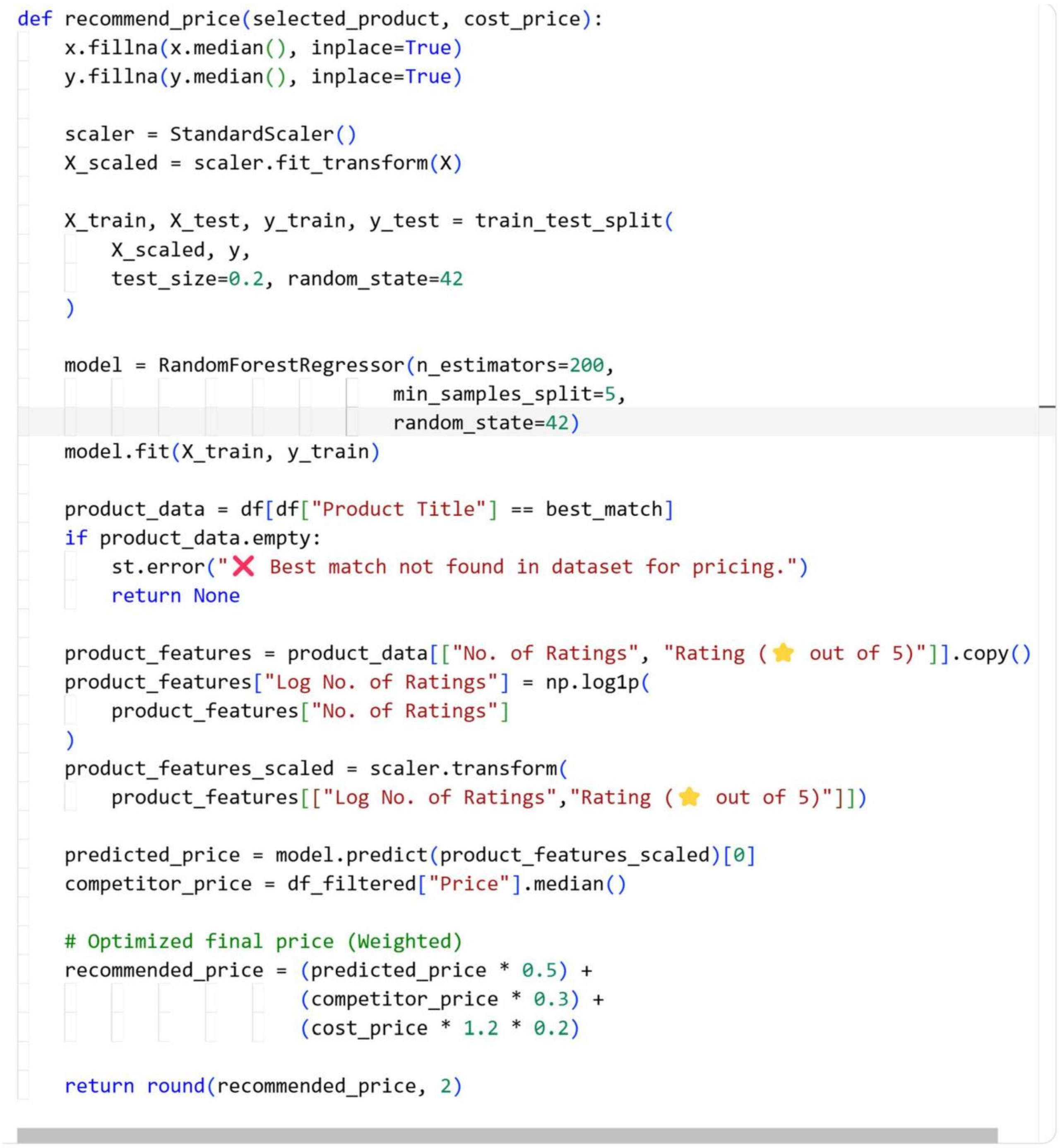
Key Features:

• **Training the RandomForest model** using historical price data.

• **Predicting competitive pricing** for new and existing products.

• **Hyperparameter tuning** to optimize model accuracy.

Output: A predicted price recommendation for sellers.



```python
def recommend_price(selected_product, cost_price):
    x.fillna(x.median(), inplace=True)
    y.fillna(y.median(), inplace=True)

    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)

    X_train, X_test, y_train, y_test = train_test_split(
        X_scaled, y,
        test_size=0.2, random_state=42
    )

    model = RandomForestRegressor(n_estimators=200,
                                  min_samples_split=5,
                                  random_state=42)
    model.fit(X_train, y_train)

    product_data = df[df["Product Title"] == best_match]
    if product_data.empty:
        st.error("❌ Best match not found in dataset for pricing.")
        return None

    product_features = product_data[["No. of Ratings", "Rating (⭐ out of 5)"]].copy()
    product_features["Log No. of Ratings"] = np.log1p(
        product_features["No. of Ratings"]
    )
    product_features_scaled = scaler.transform(
        product_features[["Log No. of Ratings","Rating (⭐ out of 5)"]])

    predicted_price = model.predict(product_features_scaled)[0]
    competitor_price = df_filtered["Price"].median()

    # Optimized final price (Weighted)
    recommended_price = (predicted_price * 0.5) +
                        (competitor_price * 0.3) +
                        (cost_price * 1.2 * 0.2)

    return round(recommended_price, 2)
```

Fig 5.2.6 Machine Learning Model Training

7. Streamlit Dashboard & Visualization Module

The **final module** presents insights through a **user-friendly Streamlit dashboard**, helping retailers make **data-driven pricing decisions**.

Key Features:

- **Interactive graphs and charts** for price trends and sentiment analysis.
- **Real-time predictions** displayed through an intuitive UI.
- **Filtering options** to analyze products by category, brand, or price range.

Output: A **fully interactive dashboard** for sellers to **optimize pricing strategies.**

5.3 Algorithm

The success of our project relies on the efficient implementation of algorithms that drive its core functionalities. These include **data extraction (web scraping), data preprocessing, feature selection, machine learning-based price prediction, and visualization**. This section describes the working principles of these algorithms.

1. Web Scraping Algorithm (Selenium & Chrome WebDriver)

Objective:

Extract real-time product pricing and customer reviews from **Flipkart, Reliance Digital, and Croma**. Since these websites dynamically load content, the algorithm uses **Selenium with Chrome WebDriver** to automate the browsing process.

Algorithm Steps:

1. **Initialize Chrome WebDriver** with proper options (e.g., headless mode for efficiency).
2. **Navigate to the target website** (e.g., Flipkart product search page).
3. **Perform search queries** for specific products.
4. **Extract product details** (name, price, and customer reviews) using XPath and CSS selectors.

5. **Handle pagination** to scrape multiple pages.

6. **Store the extracted data** in a structured format (CSV or database).

Outcome: A **clean dataset of product names, prices, and reviews** from multiple platforms.

2. Data Cleaning & Preprocessing Algorithm

Objective:

Ensure **accuracy and consistency** in the scraped data by **handling missing values, removing duplicates, and normalizing formats** before analysis.

Algorithm Steps:

1. **Convert all price values** into a standard numerical format.

2. **Remove duplicate records** (e.g., same product listed multiple times).

3. **Fill missing values** using median imputation (for price gaps).

4. **Standardize product names** to avoid mismatches across platforms.

5. **Remove outliers** (e.g., extreme price variations due to incorrect scraping).

Outcome: A **structured dataset ready for analysis**.

3. Feature Engineering Algorithm

Objective:

Extract and transform **relevant features** from raw data to improve price prediction accuracy.

Algorithm Steps:

1. **Identify key features** (product name, brand, category, historical price).

2. **Encode categorical variables** using one-hot encoding (e.g., product brand, platform).

3. **Create new features**, such as:

   ○ **Moving Average Price** (trend over time).

- **Review Sentiment Score** (derived from customer reviews using NLP).
- **Historical Price Fluctuation** (price changes over the last 30 days).

Outcome: A dataset with **well-structured features for machine learning**.

4. Machine Learning Model – RandomForest for Price Prediction

Objective:

Predict the **optimal price of a product** using a **RandomForest Regression model** trained on historical pricing data.

Algorithm Steps:

1. **Split the dataset** into training (80%) and testing (20%) sets.
2. **Train the RandomForest model** using:
   - **Independent variables**: Product features (brand, platform, review sentiment, historical price).
   - **Target variable**: Predicted price.
3. **Hyperparameter tuning** (GridSearchCV) to find the best model parameters.
4. **Evaluate model performance** using:
   - **Mean Absolute Error (MAE)**
   - **Root Mean Squared Error (RMSE)**
   - **R^2 score**
5. **Make predictions** for new product listings.

Outcome: Accurate price predictions based on market trends and competitor analysis.

5. Price Trend Analysis Algorithm

Objective:

Identify **patterns in price fluctuations** over time to help sellers make informed pricing decisions.

Algorithm Steps:

1. **Aggregate price data** over time for each product category.

2. **Apply moving averages** to smooth out fluctuations.

3. **Detect seasonal price changes** (e.g., price drops during festive sales).

4. **Visualize trends** using time-series plots.

Outcome: Insights into price trends that help sellers adjust pricing strategies dynamically.

6. Review Sentiment Analysis Algorithm

Objective:

Analyze **customer reviews** to determine **how sentiment affects pricing trends**.

Algorithm Steps:

1. **Preprocess text** (remove stopwords, lemmatization, tokenization).

2. **Apply sentiment analysis** using a **pre-trained NLP model** (e.g., VADER or TextBlob).

3. **Classify reviews** as Positive, Neutral, or Negative.

4. **Compute average sentiment score** for each product.

5. **Correlate sentiment scores with price changes** to see if higher-rated products maintain higher prices.

Outcome: A **sentiment-based insight into pricing**, helping retailers adjust pricing based on customer perception.

7. Streamlit Dashboard Algorithm

Objective:

Present **real-time pricing insights and predictions** through an interactive **Streamlit web application**.

Algorithm Steps:

1. **Initialize Streamlit** and define UI layout.

2. **Load preprocessed data and model predictions**.

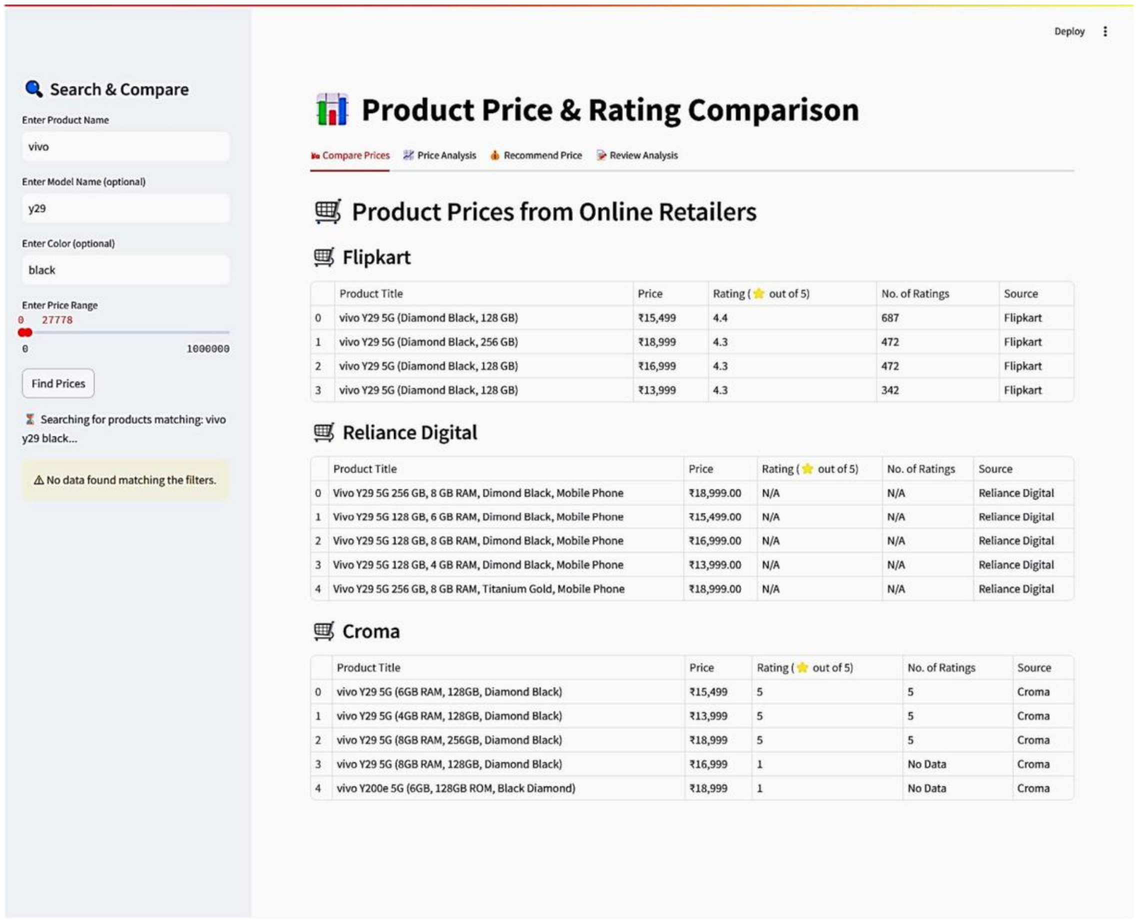
3. **Create interactive filters** for users to explore:

- **Product-wise pricing trends**
- **Predicted vs. actual prices**
- **Review sentiment impact on pricing**

4. **Display visualizations** using Matplotlib & Seaborn.

Outcome: A **fully interactive dashboard** for price monitoring and decision-making.

5.4 Screens



Search & Compare

Enter Product Name: vivo

Enter Model Name (optional): y29

Enter Color (optional): black

Enter Price Range: 0 27778 (0 – 1000000)

Find Prices

⏳ Searching for products matching: vivo y29 black...

⚠ No data found matching the filters.

Product Price & Rating Comparison

Compare Prices | Price Analysis | Recommend Price | Review Analysis

Product Prices from Online Retailers

Flipkart

	Product Title	Price	Rating (⭐ out of 5)	No. of Ratings	Source
0	vivo Y29 5G (Diamond Black, 128 GB)	₹15,499	4.4	687	Flipkart
1	vivo Y29 5G (Diamond Black, 256 GB)	₹18,999	4.3	472	Flipkart
2	vivo Y29 5G (Diamond Black, 128 GB)	₹16,999	4.3	472	Flipkart
3	vivo Y29 5G (Diamond Black, 128 GB)	₹13,999	4.3	342	Flipkart

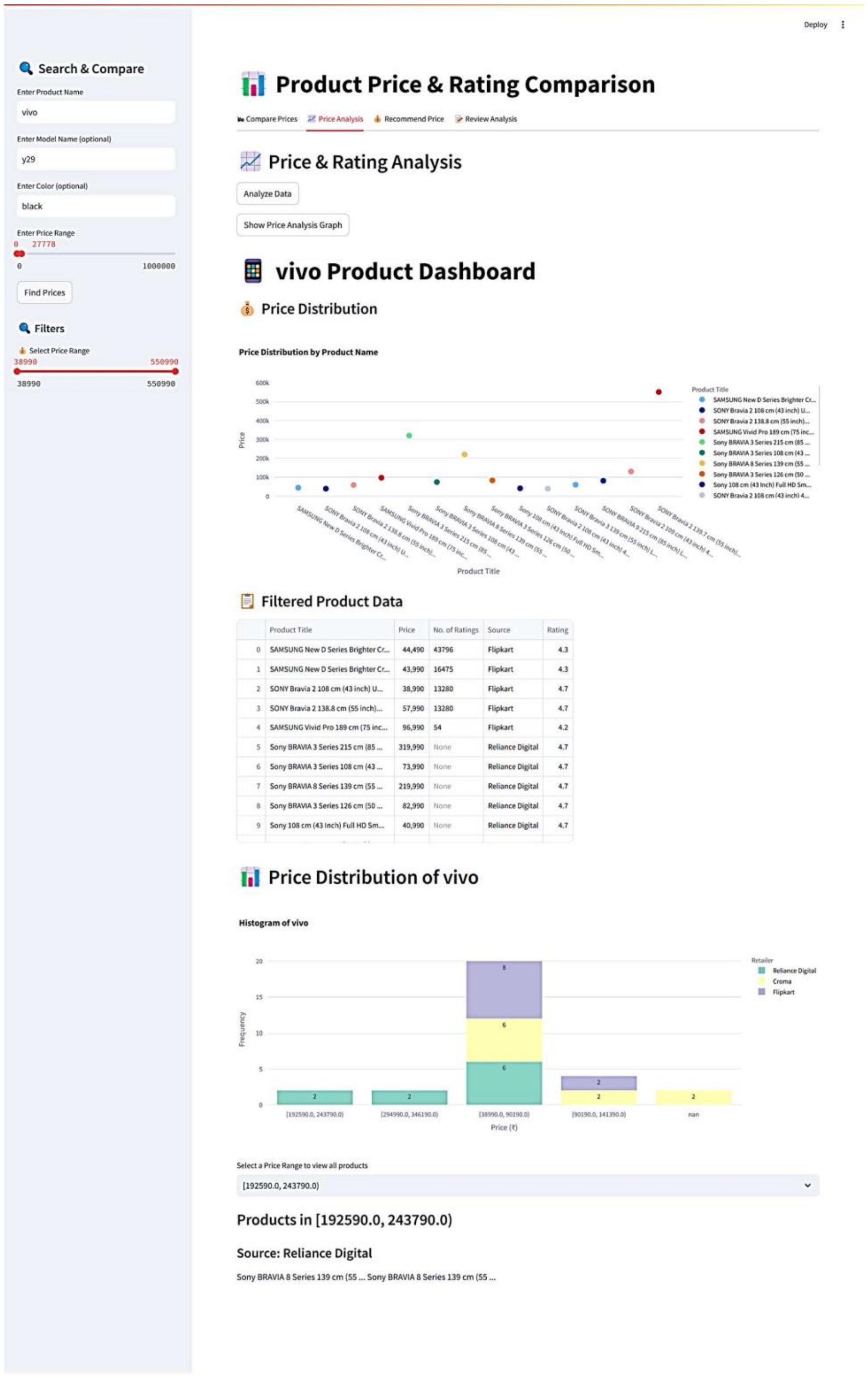
Reliance Digital

	Product Title	Price	Rating (⭐ out of 5)	No. of Ratings	Source
0	Vivo Y29 5G 256 GB, 8 GB RAM, Dimond Black, Mobile Phone	₹18,999.00	N/A	N/A	Reliance Digital
1	Vivo Y29 5G 128 GB, 6 GB RAM, Dimond Black, Mobile Phone	₹15,499.00	N/A	N/A	Reliance Digital
2	Vivo Y29 5G 128 GB, 8 GB RAM, Dimond Black, Mobile Phone	₹16,999.00	N/A	N/A	Reliance Digital
3	Vivo Y29 5G 128 GB, 4 GB RAM, Dimond Black, Mobile Phone	₹13,999.00	N/A	N/A	Reliance Digital
4	Vivo Y29 5G 256 GB, 8 GB RAM, Titanium Gold, Mobile Phone	₹18,999.00	N/A	N/A	Reliance Digital

Croma

	Product Title	Price	Rating (⭐ out of 5)	No. of Ratings	Source
0	vivo Y29 5G (6GB RAM, 128GB, Diamond Black)	₹15,499	5	5	Croma
1	vivo Y29 5G (4GB RAM, 128GB, Diamond Black)	₹13,999	5	5	Croma
2	vivo Y29 5G (8GB RAM, 256GB, Diamond Black)	₹18,999	5	5	Croma
3	vivo Y29 5G (8GB RAM, 128GB, Diamond Black)	₹16,999	1	No Data	Croma
4	vivo Y200e 5G (6GB, 128GB ROM, Black Diamond)	₹18,999	1	No Data	Croma

Fig 5.4.1 Comparing Prices


Deploy
Search & Compare
Find Prices
Filters
Analyze Data
Show Price Analysis Graph
Compare Prices
Price Analysis
Recommend Price
Review Analysis
Price Distribution by Product Name
Price
600k
500k
400k
300k
200k
100k
0
Product Title
SAMSUNG New D Series Brighter Cr...
SONY Bravia 2 108 cm (43 inch) U...
SONY Bravia 2 138.8 cm (55 inch)...
SAMSUNG Vivid Pro 189 cm (75 inc...
Sony BRAVIA 3 Series 215 cm (85 ...
Sony BRAVIA 3 Series 108 cm (43 ...
Sony BRAVIA 8 Series 139 cm (55 ...
Sony BRAVIA 3 Series 126 cm (50 ...
Sony 108 cm (43 Inch) Full HD Sm...
SONY Bravia 2 108 cm (43 inch) 4...
SONY Bravia 3 139 cm (55 inch) L...
SONY BRAVIA 9 215 cm (85 inch) L...
SONY Bravia 2 109 cm (43 inch) 4...
SONY Bravia 2 139.7 cm (55 inch)...
Histogram of vivo
Frequency
20
15
10
5
0
Retailer
Reliance Digital
Croma
Flipkart
8
6
6
2
2
2
2
2
[192590.0, 243790.0)
[294990.0, 346190.0)
[38990.0, 90190.0)
[90190.0, 141390.0)
nan
Price (₹)

Product Price & Rating Comparison

Enter Product Name: vivo

Enter Model Name (optional): y29

Enter Color (optional): black

Enter Price Range: 0 – 27778 (0 to 1000000)

Select Price Range: 38990 – 550990 (38990 to 550990)

Price & Rating Analysis

vivo Product Dashboard

Price Distribution

Filtered Product Data

	Product Title	Price	No. of Ratings	Source	Rating
0	SAMSUNG New D Series Brighter Cr...	44,490	43796	Flipkart	4.3
1	SAMSUNG New D Series Brighter Cr...	43,990	16475	Flipkart	4.3
2	SONY Bravia 2 108 cm (43 inch) U...	38,990	13280	Flipkart	4.7
3	SONY Bravia 2 138.8 cm (55 inch)...	57,990	13280	Flipkart	4.7
4	SAMSUNG Vivid Pro 189 cm (75 inc...	96,990	54	Flipkart	4.2
5	Sony BRAVIA 3 Series 215 cm (85 ...	319,990	None	Reliance Digital	4.7
6	Sony BRAVIA 3 Series 108 cm (43 ...	73,990	None	Reliance Digital	4.7
7	Sony BRAVIA 8 Series 139 cm (55 ...	219,990	None	Reliance Digital	4.7
8	Sony BRAVIA 3 Series 126 cm (50 ...	82,990	None	Reliance Digital	4.7
9	Sony 108 cm (43 Inch) Full HD Sm...	40,990	None	Reliance Digital	4.7

Price Distribution of vivo

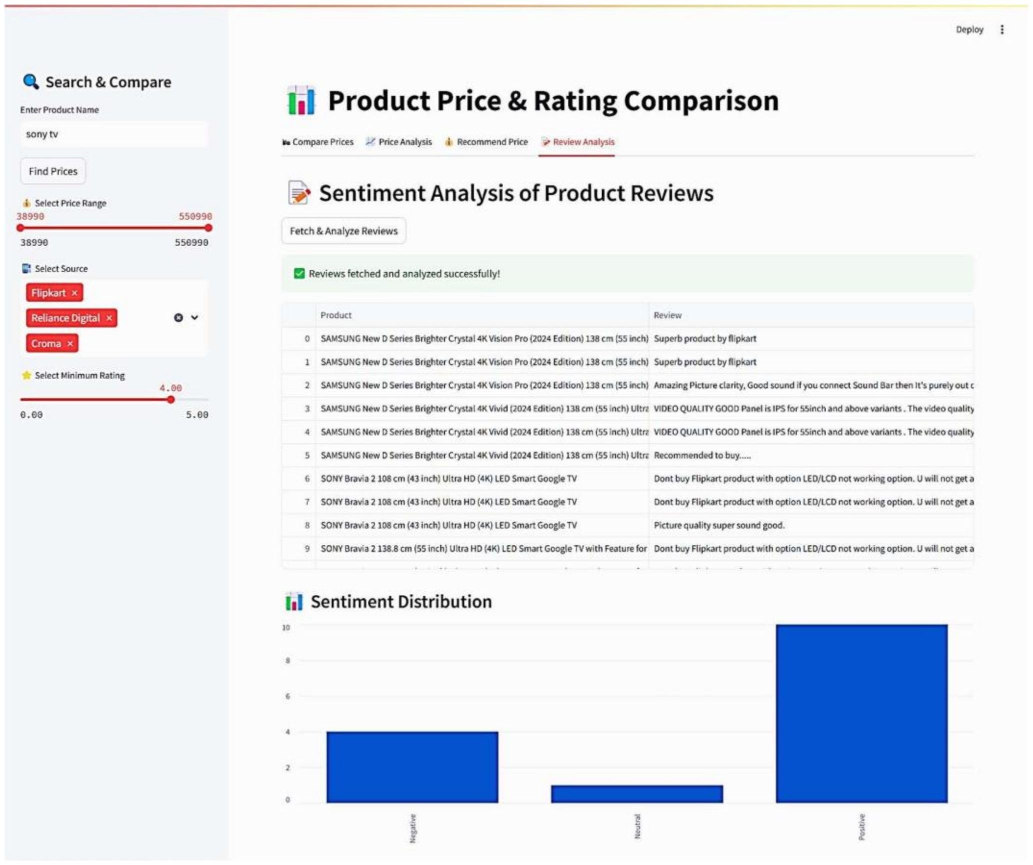
Select a Price Range to view all products: [192590.0, 243790.0)

Products in [192590.0, 243790.0)

Source: Reliance Digital

Sony BRAVIA 8 Series 139 cm (55 ... Sony BRAVIA 8 Series 139 cm (55 ...

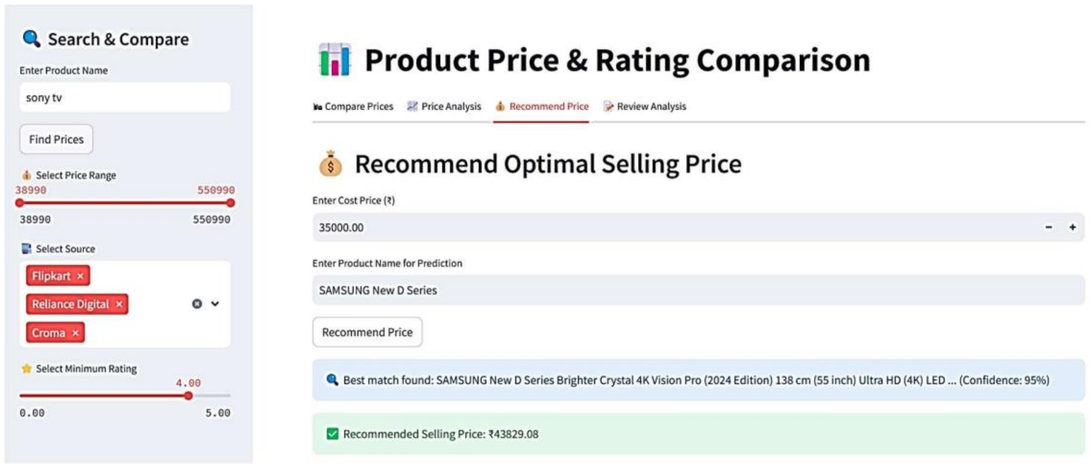
Fig 5.4.2 Price Analysis



Reviews fetched and analyzed successfully!

	Product	Review
0	SAMSUNG New D Series Brighter Crystal 4K Vision Pro (2024 Edition) 138 cm (55 inch)	Superb product by flipkart
1	SAMSUNG New D Series Brighter Crystal 4K Vision Pro (2024 Edition) 138 cm (55 inch)	Superb product by flipkart
2	SAMSUNG New D Series Brighter Crystal 4K Vision Pro (2024 Edition) 138 cm (55 inch)	Amazing Picture clarity, Good sound if you connect Sound Bar then It's purely out c
3	SAMSUNG New D Series Brighter Crystal 4K Vivid (2024 Edition) 138 cm (55 inch) Ultra	VIDEO QUALITY GOOD Panel is IPS for 55inch and above variants . The video quality
4	SAMSUNG New D Series Brighter Crystal 4K Vivid (2024 Edition) 138 cm (55 inch) Ultra	VIDEO QUALITY GOOD Panel is IPS for 55inch and above variants . The video quality
5	SAMSUNG New D Series Brighter Crystal 4K Vivid (2024 Edition) 138 cm (55 inch) Ultra	Recommended to buy.....
6	SONY Bravia 2 108 cm (43 inch) Ultra HD (4K) LED Smart Google TV	Dont buy Flipkart product with option LED/LCD not working option. U will not get a
7	SONY Bravia 2 108 cm (43 inch) Ultra HD (4K) LED Smart Google TV	Dont buy Flipkart product with option LED/LCD not working option. U will not get a
8	SONY Bravia 2 108 cm (43 inch) Ultra HD (4K) LED Smart Google TV	Picture quality super sound good.
9	SONY Bravia 2 138.8 cm (55 inch) Ultra HD (4K) LED Smart Google TV with Feature for	Dont buy Flipkart product with option LED/LCD not working option. U will not get a

Fig 5.4.3 Price recommendation



Best match found: SAMSUNG New D Series Brighter Crystal 4K Vision Pro (2024 Edition) 138 cm (55 inch) Ultra HD (4K) LED ... (Confidence: 95%)

Recommended Selling Price: ₹43829.08

Fig 5.4.4 Review Analysis

6. SYSTEM TESTING

6.1 Introduction

Software testing is a fundamental process in the Software Development Life Cycle (SDLC) that ensures an application meets predefined requirements and functions correctly. It involves evaluating the software through various testing techniques to identify defects, verify functionality, and improve overall quality before deployment. Effective software testing helps deliver reliable, secure, and high-performance software that aligns with user expectations and business objectives.

Historically, software development lacked a structured approach to testing, leading to significant failures, financial losses, and reputational damage. Software testing emerged to address these challenges by offering systematic validation and verification processes. The key reasons for its inception include:

Increasing complexity of software systems: As applications became more advanced, the need for rigorous testing grew to ensure reliability and performance.

- **Cost-effectiveness of early defect detection**: Fixing bugs during development is significantly cheaper than addressing issues after deployment.
- **Rising security concerns**: The prevalence of cyber threats necessitates security testing to protect sensitive data and prevent vulnerabilities.
- **Growing demand for user-centric software**: Users expect high-quality applications that are easy to use, efficient, and free from critical errors.

Over time, software testing has evolved into a discipline encompassing various methodologies, tools, and best practices to improve software quality. Software testing is an integral phase of SDLC, typically occurring at multiple stages to ensure quality control throughout the development lifecycle.
The key roles of software testing in SDLC include:

- **Ensuring software correctness and reliability**: Verifies that the application behaves as expected under various conditions.
- **Detecting and preventing defects early**: Identifies issues before they reach production, reducing costs and improving product stability.
- **Validating functional and non-functional requirements**: Confirms that the software meets all business and user requirements, including security, usability, and performance aspects.
- **Enhancing user experience and customer satisfaction**: Ensures that software is intuitive, responsive, and free from critical issues that could impact usability.

- **Supporting continuous integration and deployment (CI/CD)**: Plays a crucial role in Agile and DevOps methodologies by automating testing and enabling faster releases.

By integrating software testing throughout the development process, organizations can maintain high-quality standards and minimize risks associated with software failures.

Approaches to Software Testing

Software testing can be approached in different ways based on project requirements and objectives. Common approaches include:

1. **Black Box Testing** - Focuses on evaluating software functionality without considering internal code structures. Used for user interface testing, API testing, and system testing.
2. **White Box Testing** - Examines the internal logic and structure of the software. Primarily performed by developers to ensure code correctness and optimize performance.
3. **Manual Testing** - Involves human testers executing test cases to evaluate system behavior, usability, and responsiveness.
4. **Automated Testing** - Uses software tools and scripts to execute test cases automatically, improving efficiency, accuracy, and repeatability.
5. **Regression Testing** - Ensures that new code changes do not negatively affect existing functionality.

Each approach has its advantages, and a combination of these methods is often used to achieve comprehensive test coverage.

Methods of Software Testing

Various testing methods help ensure that software meets quality and performance standards. These include:

1. **Functional Testing** - Verifies that the software meets business and functional requirements.
2. **Performance Testing** - Assesses the software's speed, responsiveness, and stability under different conditions.
3. **Security Testing** - Identifies vulnerabilities to prevent data breaches and security threats.
4. **Usability Testing** - Evaluates user-friendliness and accessibility.
5. **Compatibility Testing** - Ensures software functions across various devices, browsers, and operating systems.
6. **Unit Testing** - Tests individual components or modules of the application.
7. **Integration Testing** - Validates interactions between different system modules.
8. **System Testing** - Evaluates the complete system as a whole to ensure compliance with requirements.
9. **Acceptance Testing** - Determines whether the software is ready for deployment by assessing its alignment with business needs and user expectations.

A combination of these testing methods enhances software reliability and reduces the risk of failures.

Understanding software testing involves familiarity with key terms:

- **Test Plan**: A document outlining the testing strategy, scope, and resources.
- **Test Case**: A set of conditions used to verify specific software functionality.
- **Test Script**: An automated test case executed by testing tools.
- **Defect/Bug**: An error in the software that affects functionality or performance.
- **Test Environment**: The setup where testing is conducted, including hardware, software, and configurations.
- **Smoke Testing**: A basic test to check if the application is stable enough for further testing.
- **Sanity Testing**: Focuses on verifying specific functionalities after minor changes.
- **Alpha Testing**:Conducted internally before releasing the software to end users.
- **Beta Testing**: Performed by real users in a controlled environment to gather feedback before full deployment.

These terminologies help stakeholders communicate effectively and streamline the testing process.

Despite its benefits, software testing presents several challenges:

- **Time and resource constraints**: Comprehensive testing requires significant time, expertise, and infrastructure.
- **Complex test scenarios**: Advanced applications involve intricate interactions that are difficult to test thoroughly.
- **Test data management**: Creating and maintaining test data that mimics real-world scenarios can be challenging.
- **Frequent requirement changes**: Agile and DevOps environments require testers to adapt to evolving requirements quickly.
- **Automation maintenance**: Automated tests require regular updates to stay relevant as software evolves.

Overcoming these challenges requires strategic planning, robust test automation, and collaboration between development and testing teams.

Software testing is a critical component of SDLC that ensures software reliability, security, and performance. By employing diverse approaches, methods, and best practices, organizations can minimize risks, enhance user satisfaction, and deliver high-quality software products. As technology continues to evolve, software testing remains essential in maintaining software integrity and supporting successful deployments.

6.2 Testing methods

System testing involves evaluating a fully integrated software system to ensure its proper functionality. Typically, a computer system comprises both software and hardware components that must work together seamlessly. While software is developed in individual units, it must be integrated with other software and hardware elements to form a complete, functional system. This means that software alone cannot perform tasks—it requires compatible hardware to execute operations effectively.

System testing encompasses a series of test types designed to assess the overall performance of an integrated software system against specified requirements. It involves verifying the end-to-end workflow of an application from a user's perspective, ensuring that all essential modules function as expected. This type of testing simulates real-world usage by evaluating the software in an environment that closely resembles the production setup.

There are two primary approaches to software testing:

White Box Testing, which examines the internal code structure to design test cases, and Black Box Testing, which focuses on user interactions and GUI-based testing without considering the internal workings of the software.

The key methodologies used in software testing include:

Unit Testing – Testing individual components or modules.
Integration Testing – Ensuring seamless interaction between integrated units.
Validation Testing – Confirming the software meets specified requirements.
White Box Testing – Testing based on internal code logic.
Black Box Testing – Evaluating the system from a user's perspective

Unit Testing :

Unit testing is a crucial process in software development that focuses on verifying the smallest units of a software system—individual functions, modules, or components. It ensures that each unit functions correctly before being integrated with other parts of the system. Unit testing involves exercising specific paths in a module's control structure to achieve complete coverage and maximum error detection. This approach helps developers validate code functionality, detect errors early, and maintain high-quality code throughout the development cycle.

Unit testing is the first and foundational level of testing in the **Software Development Life Cycle (SDLC)** and **Software Testing Life Cycle (STLC)**. It falls under **White Box Testing**, where developers examine the internal logic and structure of the code. In an ideal scenario, developers perform unit testing during the coding phase before integration testing. However, in real-world scenarios, QA engineers may also conduct unit tests due to time constraints or the reluctance of developers to test their own code.

As a critical part of **system testing**, unit testing helps identify defects before they can cause failures in the integrated system. By testing individual components before integration, it reduces the debugging effort required in later stages, ensuring a smooth transition to **integration testing, system testing, and acceptance testing.**

Benefits of Unit Testing in the Software Development Life Cycle (SDLC)

Unit testing provides several advantages throughout the SDLC:

- **Early Bug Detection**: Identifies and fixes defects at an early stage, reducing overall debugging time.
- **Code Maintainability**: Allows developers to refactor and modify code with confidence.
- **Enhanced Code Quality**: Encourages modular and structured code, leading to better software architecture.
- **Faster Development Cycle**: Reduces debugging and reworking time by catching errors early.
- **Improved Collaboration**: Clearly defines expected behaviors, facilitating better team coordination.
- **Documentation**: Acts as documentation by outlining function expectations under different conditions.

Code Reusability: Enables migration of both code and tests to new projects, reducing development effort.

Types of Unit Testing

1. **Manual Unit Testing**: Performed manually by developers to validate individual components.
2. **Automated Unit Testing**: Performed using testing frameworks to automate test case execution, ensuring consistency and repeatability.

Unit Testing in the Price Recommendation System

For the **Price Recommendation System**, unit testing is applied to various modules to verify correctness. Key areas for unit testing include:

1. **Data Fetching (fetch.py)**

- Test the fetch_product_data function by mocking web requests to ensure correct extraction of product details.
- Validate that product details such as titles, prices, and ratings are fetched accurately from different e-commerce websites.
- Ensure that error handling mechanisms work correctly when fetching data from unavailable or malformed sources.

2. **Data Analysis (analyze.py)**

- Test the data preprocessing functions to verify correct handling of missing values, duplicates, and data formatting.
- Validate price recommendation algorithms to ensure they return optimal price predictions based on input parameters.
- Check if statistical models produce expected outputs based on given historical price data.

3. **Machine Learning Model Selection and Training (model_selection_training.py)**

- Test the train-test split logic to ensure correct data partitioning.
- Validate that machine learning models are trained correctly and return expected accuracy and performance metrics.
- Ensure that feature selection and hyperparameter tuning functions operate as expected.

4. **Visualization (visualization.py)**

- Test price distribution plots and competitor price comparisons for correct data representation.
- Validate that the visualization module handles missing values gracefully without crashes.
- Ensure that UI elements update dynamically based on changes in the data.

5. **Streamlit Application (app.py)**

- Test UI input handling by verifying that user-entered product names are correctly processed.
- Mock API responses to simulate different conditions and validate error handling mechanisms.
- Ensure that results displayed in the UI match expected outputs from the backend modules.

Unit testing plays a crucial role in ensuring the reliability, maintainability, and efficiency of the Price Recommendation System. By implementing structured unit tests, developers can detect defects early, improve code quality, and create a more scalable and stable application. Integrating unit testing into the SDLC ensures that each module functions as expected, enhancing the overall performance and user experience of the system.

Integration Testing:

Integration testing is a software testing phase that focuses on assessing the interaction between different modules or components of an application. It ensures that combined parts function together as expected. Unlike unit testing, which verifies individual components in isolation, integration testing evaluates the system as a whole by checking the data flow and interoperability between modules. The primary goal is to identify issues related to data exchange, interface mismatches, and inconsistencies that may arise when multiple units are integrated.

Benefits of Integration Testing

Integration testing provides several advantages, including:

- **Early Detection of Issues:** Identifies defects related to module interactions before the system enters full-scale testing.
- **Improved System Reliability:** Ensures that modules work together seamlessly, reducing the likelihood of integration failures in production.
- **Validates System Requirements:** Confirms that the combined components meet the functional and non-functional requirements of the application.
- **Better Debugging and Maintenance:** Helps isolate and fix integration-related issues efficiently, improving maintainability.

Enhanced Performance: Optimizes data flow and interface handling, leading to a robust and efficient application.

Ways of Performing Integration Testing

There are various strategies for conducting integration testing. Below are the key approaches, including their application to the given price recommendation system.

1. Big Bang Testing
2. Top-Down Testing
3. Bottom-Up Testing
4. Incremental Testing

Big Bang Testing

Big Bang Testing involves integrating all modules simultaneously and testing the complete system in one go. This method assumes that all components are ready before testing begins and does not follow a phased approach.

What and How:

- All individual modules are first developed and verified independently.
- Once development is complete, they are integrated to form the entire system.
- The complete system is tested as a single unit to ensure that all modules interact correctly.
- The test cases focus on end-to-end functionality, ensuring that data flows correctly between integrated modules.

To integrate with the project, all core components responsible for data extraction, preprocessing, model training, visualization, and user interaction are integrated simultaneously. The system is then tested as a whole to ensure that data flows seamlessly from fetching product details to generating price recommendations, requiring all modules to interact without unexpected errors.

This approach provides a complete picture of the system's functionality, making it suitable for small projects with minimal dependencies and efficient when modules have already been thoroughly unit tested. However, debugging can be challenging since multiple modules are tested together, making it difficult to isolate issues related to specific module interactions. Additionally, this method requires all modules to be fully developed before integration testing can begin.

Top-Down Testing

Top-Down Testing starts by testing higher-level modules before integrating lower-level modules incrementally. This ensures that core functionalities are validated early before incorporating dependent modules.

What and How:

- The system is built in a hierarchical manner, with testing starting from the main control module.
- Lower-level components are gradually integrated and tested.
- Stubs (temporary placeholders) are used to simulate lower modules when they are not yet developed.
- This approach ensures that the backbone of the application is stable before integrating supporting components.

For the given project, testing should begin with the core interface responsible for user interaction. Initially, backend processes can be simulated using stubs before integrating actual data processing and analysis components. Backend processing, data fetching, and visualization modules should be incrementally integrated and validated to ensure the system remains functional as additional modules are added.

This approach helps identify integration issues in critical components early, ensures stability before integrating dependent modules, and reduces the risk of major failures at later stages. However, it requires stubs to simulate lower-level components, which can be time-consuming if a large number of such modules need to be integrated later. Additionally, some defects may not surface until lower-level modules are fully integrated.

Bottom-Up Testing

Bottom-Up Testing begins with testing the lower-level components first before progressively integrating and testing higher-level modules.

What and How:

- Lower-level modules are tested individually before being combined into more complex subsystems.
- Test drivers (temporary higher-level modules) simulate interactions with unimplemented components.
- As each new module is integrated, testing ensures that data flows correctly between components.
- Once all components are verified, the final system is assembled and tested as a whole.

For the given project, testing should start with the components responsible for fundamental tasks such as data retrieval and analysis. Interactions with higher-level functionalities can be simulated using test drivers, allowing for a gradual integration of the interface and other system layers while ensuring that each addition does not disrupt existing functionality. Final testing is conducted once all modules are fully integrated.

This approach helps in the early identification of foundational module issues, ensures that lower-level components are stable before full integration, and simplifies debugging due to incremental testing. However, higher-level system issues may not be detected early, requiring additional test drivers to simulate upper modules, and delaying full system testing until later stages.

Validation Testing

Validation testing is a critical process in the software development lifecycle (SDLC) that ensures a system meets the business and user requirements. It involves assessing whether the software behaves as expected and fulfills its intended purpose. Validation testing verifies that the product is fit for use and performs its designated functions under specified conditions.

Unlike verification, which focuses on ensuring that the software is built correctly, validation emphasizes building the correct software. It is often conducted in the later stages of development and includes techniques like functional, usability, and performance testing to ensure the product delivers value to its users.

Validation testing forms an essential part of quality assurance, aiming to detect defects, ensure compliance with requirements, and ultimately confirm the system's readiness for deployment.

Role of Validation Testing in System Testing and SDLC

System Testing

Validation testing plays a significant role in system testing, which evaluates the complete and integrated software system. It ensures that:

1. The system functions as a whole.
2. It satisfies the functional and non-functional requirements specified during the requirements gathering phase.
3. It operates effectively under real-world conditions.

System testing typically involves:

- **Functional Testing:** Validates that specific functionalities of the system meet the requirements.
- **End-to-End Testing:** Ensures that all components of the system interact correctly.
- **Regression Testing:** Confirms that changes in code do not negatively impact existing features.

Software Development Lifecycle (SDLC)

Validation testing is integrated into the SDLC phases, particularly during testing and maintenance:

1. **Requirement Analysis Phase:** Validation begins with identifying and documenting the user's needs, forming the baseline for testing.

2. **Design Phase:** Ensures that the architecture and design align with the specified requirements.
3. **Development Phase:** Focuses on creating test cases and preparing for validation.
4. **Testing Phase:** Conducts actual validation through various testing techniques.
5. **Deployment and Maintenance Phase:** Ensures the deployed system continues to meet user expectations.

By verifying alignment with requirements, validation testing minimizes the risk of delivering a product that fails to satisfy stakeholders.

Validation Testing Approaches

General Approaches

1. **Manual Testing:** Involves human testers performing predefined test cases to validate the system's behavior against requirements.
2. **Automated Testing:** Utilizes tools and scripts to execute test cases, enabling efficient and repeatable validation.
3. **Black-Box Testing:** Tests the system without knowledge of internal code structures, focusing on inputs and expected outputs.
4. **Gray-Box Testing:** Combines black-box and white-box approaches to validate both functionality and internal mechanisms.
5. **Exploratory Testing:** Relies on tester expertise to explore the system's functionality without predefined test cases.
6. **Acceptance Testing:** Includes user acceptance testing (UAT) and operational acceptance testing to ensure the system meets business needs and is ready for deployment.

Requirements for Validation Testing

Effective validation testing requires:

1. **Clear and Comprehensive Requirements:** Well-documented user and functional requirements form the foundation for validation.
2. **Test Environment:** A controlled and representative environment for executing tests.
3. **Test Plan and Cases:** Detailed plans and scripts to guide testing activities.
4. **Traceability Matrix:** Ensures coverage of all requirements in the validation process.
5. **Defect Management System:** Tracks and resolves issues identified during validation.

Validation Testing Approaches for the Price Recommendation Project

The Price Recommendation System involves multiple components, including data fetching, analysis, visualization, and machine learning models. Validation testing for this project can be approached as follows:

1. Functional Validation

- Verify that the data fetching module retrieves accurate and complete product details from Flipkart, Croma, and Reliance Digital.
- Test the analysis module to ensure correct cleaning, preprocessing, and insights generation.
- Validate the visualization module to ensure the generated charts accurately represent the data.
- Confirm that price recommendations are logical, aligned with the analysis, and meet user expectations.

2. Integration Testing

- Ensure seamless integration of modules (fetch.py, analyze.py, and visualization.py) with the Streamlit app (app.py).
- Test interactions between the user interface and the backend components.

3. Regression Testing

- Ensure modifications to scraping logic (e.g., XPath updates in config.json) do not impact other functionalities.
- Test model updates in model_selection_training.py to verify that predictive accuracy remains consistent.

4. Usability Testing

- Validate that the Streamlit app is intuitive and user-friendly.
- Ensure that users can easily input product names, view fetched data, and interpret visualizations and recommendations.

5. Performance Testing

- Measure the time taken to fetch, analyze, and visualize data for a given product.
- Validate the system’s ability to handle multiple concurrent users or large datasets.

6. Acceptance Testing

- Conduct user acceptance testing to validate that the recommendations align with stakeholder requirements and real-world scenarios.

7. Test Data and Environment Setup

- Use realistic test data stored in product_data.csv to simulate fetching and analysis processes.
- Set up the test environment to replicate conditions on different operating systems and browsers.

8. Automated Testing

- Implement automation scripts to validate key functionalities such as scraping, preprocessing, and model predictions.
- Use tools like Selenium for browser automation and Pytest for unit and integration tests.

Validation testing ensures the delivery of a robust, user-friendly, and functional Price Recommendation System. By integrating comprehensive testing strategies throughout the SDLC, the system can achieve higher reliability, user satisfaction, and business success. For this project, combining functional, usability, and automated testing approaches will effectively validate all components, guaranteeing a seamless and effective solution for e-commerce retailers.

White Box Testing

White Box Testing, also known as clear box testing, glass box testing, or structural testing, is a software testing technique that examines the internal structures, logic, and workings of a software application. Unlike black box testing, which focuses on input and output without knowledge of the internal code, white box testing allows testers to scrutinize the code, data flow, control flow, and algorithms.

White Box Testing involves understanding the source code, identifying test cases based on the code’s functionality, and ensuring all branches and paths are tested. This testing is mainly performed by developers and quality assurance engineers with programming knowledge.

Requirements for White Box Testing

White Box Testing requires the following:

• **Access to the source code**: Testers must have full knowledge and access to the codebase.

• **Understanding of programming and logic**: Testers should have a solid understanding of programming languages used in the application.

• **Tools for static and dynamic analysis**: Tools such as JUnit, NUnit, Selenium, and White can help in automating tests.

• **Test cases covering all logical paths**: Every decision, condition, and loop should be tested.

Knowledge of code vulnerabilities: Testers should be able to identify security risks, such as buffer overflows and SQL injection.

White Box Testing Techniques

Several techniques are used in White Box Testing to ensure thorough validation of the internal logic of the software:

a. Statement Coverage

- Ensures every line of code is executed at least once.
- Helps detect unused statements and unreachable code.

b. Branch Coverage

- Validates that all possible branches (e.g., if-else conditions) in the code are executed.
- Ensures no logical path is skipped.

c. Path Coverage

- Tests all possible paths in a program, covering all possible conditions and loops.
- Ensures robustness by validating every decision-making process.

d. Loop Testing

- Focuses on validating loops, including simple, nested, and conditional loops.
- Helps identify infinite loops and performance issues.

e. Condition Coverage

- Ensures that each condition within the decision statements (e.g., if, switch) is tested for true and false values.
- Identifies logical errors in complex conditions.

f. Data Flow Testing

- Tracks the use of variables and ensures correct initialization and deletion.

Detects anomalies such as uninitialized variables and memory leaks.

Advantages of White Box Testing

White Box Testing provides several benefits to software development and quality assurance:

- **Thorough testing**: Ensures complete code coverage and logic validation.
- **Early defect detection**: Identifies bugs and security vulnerabilities at the early stages of development.
- **Optimization of code**: Helps in improving code efficiency and eliminating redundant logic.
- **Better test case design**: Since testers understand the internal logic, they can create more effective test scenarios.
- **Security enhancement**: Helps in identifying security flaws such as SQL injections and unauthorized access.

Disadvantages of White Box Testing

Despite its advantages, White Box Testing has some limitations:

• **Time-consuming**: Requires thorough analysis and testing of every part of the code, making it time-intensive.

• **Expensive**: Demands skilled testers with programming knowledge, increasing costs.

Difficult to scale: Large and complex applications may require significant effort to achieve complete code coverage.

Dependency on code knowledge: Only developers or testers with knowledge of the internal code can perform White Box Testing.

Limited real-world testing: Focuses on internal logic rather than user experience, potentially missing usability issues.

White Box Testing is an essential software testing technique that ensures the internal logic and code quality of an application are thoroughly validated. It is highly effective in detecting security vulnerabilities, optimizing performance, and ensuring all code paths are executed. However, due to its complexity and resource requirements, it is best used alongside Black Box Testing to achieve comprehensive software quality assurance.

For applications such as the **Regression-Analysis-Based Pricing Recommendation System**, White Box Testing can be crucial in ensuring the accuracy of data analysis, price recommendations, and proper functioning of web scraping mechanisms. Using automated testing tools and well-defined test cases, developers can enhance the reliability and security of the pricing recommendation system.

Black Box Testing

Black Box Testing is a software testing technique that evaluates the functionality of an application without delving into its internal structures or code. Testers focus on the input and output of the software system rather than how the system processes the input. This type of testing ensures that an application meets user requirements and functions as expected. It is also known as behavioral testing because it examines the software’s behavior under different conditions.

This type of testing is crucial in software development because it allows testers to verify whether an application functions as intended without being influenced by the internal workings of the codebase. The goal is to simulate real-world user interactions and identify defects that may impact usability, functionality, or performance.

Requirements for Black Box Testing

Black Box Testing requires the following:

• **Functional Specifications**: A document detailing the intended behavior of the application.

• **Test Cases**: A set of test scenarios derived from user requirements.

• **Test Data**: Input values to evaluate the response of the system.

• **Expected Results**: Predetermined outcomes based on system requirements.

Testing Tools (Optional): Automated or manual tools like Selenium, QTP, or TestComplete can be used.

Well-defined Requirements: Clearly documented requirements ensure testers can define accurate test cases.

User Stories and Use Cases: Help understand expected application behavior from an end-user perspective.

To successfully execute Black Box Testing, it is crucial to have well-structured test cases, appropriate testing environments, and properly defined success criteria. Additionally, clear documentation of test execution results helps in bug tracking and issue resolution.

Techniques Used in Black Box Testing

Several techniques are used to perform Black Box Testing, including:

Equivalence Partitioning

This technique divides input data into different partitions or classes, assuming that all values in a partition will produce the same output. It helps reduce redundant test cases by ensuring that at least one value from each class is tested. For example, if an application accepts input values from 1 to 100, test cases can be designed for three partitions: values below 1 (invalid input), values between 1 and 100 (valid input), and values above 100 (invalid input).

Boundary Value Analysis (BVA)

Testing is performed at the boundaries of input ranges since defects often occur at boundary limits. This method ensures that edge cases are tested to catch potential off-by-one errors. For instance, if an application accepts input between 1 and 100, test values such as 0, 1, 100, and 101 are selected to verify system behavior at boundary conditions.

Decision Table Testing

A decision table represents different input conditions and their corresponding system responses. It helps ensure comprehensive coverage of input combinations by mapping different conditions to their expected outcomes. For example, in an online shopping application, a decision table can be used to test different combinations of discount eligibility criteria, such as membership status, purchase amount, and promotional codes.

State Transition Testing

This technique is used when an application has different states and transitions between them based on inputs. It is particularly useful for applications that follow defined workflows or processes. For example, a banking application may transition between different states like 'Account Created,' 'Active,' 'Locked,' and 'Closed,' depending on user interactions.

Error Guessing

A tester applies their intuition and experience to guess where defects might occur. It is a less structured but effective technique that relies on the tester's knowledge of common mistakes made in software development. For example, an experienced tester might predict errors related to invalid login attempts, missing required fields, or incorrect data formatting.

Advantages of Black Box Testing

• **No Need for Internal Code Knowledge**: Testers do not require programming expertise, making it easier for non-developers to participate in testing.

• **Focus on User Experience**: Ensures that the application meets user expectations and functions correctly in real-world scenarios.

• **Applicable to Various Testing Levels**: Can be used for unit, integration, system, and acceptance testing.

• **Helps Identify Missing Requirements**: Since testing is based on user expectations, it can highlight missing functionalities or unexpected behaviors.

• **Effective for Large Systems**: It is particularly useful for testing large and complex applications where analyzing source code is impractical.

Encourages Automation: Many Black Box Testing techniques can be automated, reducing manual effort and increasing testing efficiency.

Disadvantages of Black Box Testing

• **Limited Coverage**: Since internal logic is not examined, some paths may remain untested.

• **Difficult to Pinpoint Root Cause of Defects**: Without insight into the code, diagnosing issues can be challenging and may require White Box Testing for debugging.

• **Repetitive Testing**: Similar test cases may be executed multiple times, leading to redundancy.

• **High Dependence on Test Cases**: The effectiveness of testing depends on how well test cases are designed. Poorly written test cases can lead to gaps in testing coverage.

Inability to Detect Code-Level Errors: Since Black Box Testing focuses only on functionality, it may miss security vulnerabilities or performance inefficiencies that can only be identified through code analysis.

Black box testing is useful during functional testing to validate system requirements and ensure expected behavior. It is also employed in acceptance testing to confirm software usability and compliance with business needs. This approach is particularly beneficial when testing web-based applications for UI/UX consistency and overall user experience. Additionally, black box testing plays a crucial role in automated regression testing to verify that new changes do not introduce unexpected defects. Furthermore, it is essential in compatibility testing to ensure the application functions correctly across different devices and browsers.

Black Box Testing is an essential approach in software testing, ensuring that applications function correctly from an end-user perspective. By utilizing different testing techniques and tools, testers can validate software functionality without delving into code. However, it is essential to complement Black Box Testing with White Box Testing for comprehensive test coverage.

With the increasing complexity of modern applications, Black Box Testing continues to play a crucial role in software development, enabling testers to identify defects, validate business requirements, and improve software quality before deployment. Proper test planning, execution, and automation can further enhance the effectiveness of Black Box Testing in delivering high-quality software products.

6.1 Test Cases

Test Description	Expected Result	Actual Result	Success/ Fail
Hardware Compatibility			
Verify system meets minimum hardware requirements	System should have at least 8GB RAM, 4-core CPU, and 256GB SSD	System meets the requirements	Success
Software Installation and Configuration			
Install Python 3.8+	Python 3.8+ should be installed successfully	Python 3.9 installed successfully	Success
Install required Python packages	All packages in requirements.txt shoul d be installed without errors	All packages installed successfully	Success
Data Fetching			
Fetch product data from Flipkart	Should return a list of products with title, price, rating, and ratings count	Successfully fetched product data	Success
Fetch product data from Croma	Should return a list of products with title, price, rating, and ratings count	Successfully fetched product data	Success
Fetch product data from Reliance Digital	Should return a list of products with title, price, rating, and ratings count	Successfully fetched product data	Success
Popup Handling			
Handle alert popup during data fetch	Alert should be detected and dismissed	Alert detected and dismissed successfully	Success

Handle no alert scenario during data fetch	Function should complete without errors	Function completed without errors	Success
Data Analysis			
Preprocess fetched data	Data should be cleaned and ready for analysis	Data cleaned successfully	Success
Recommend optimal price based on analysis	Should return a recommended price based on input cost price	Recommended price returned successfully	Success
Visualization			
Display price distribution graph	Graph should display price distribution of products	Graph displayed successfully	Success
Display filtered product data	Table should display filtered product data based on user input	Table displayed successfully	Success
Error Handling			
Handle missing XPath configurations	Should display an error message and stop execution	Error message displayed and execution stopped	Success
Handle no data found for product	Should display a warning message	Warning message displayed	Success

7. CONCLUSION

Our project, *"Regression Analysis-Based Pricing Recommendations for E-Commerce Retailers,"* is a testament to the power of data-driven decision-making in modern online retail. By harnessing a combination of advanced technologies, we have developed a system capable of not only gathering and analyzing product data but also generating strategic pricing recommendations. This project bridges the gap between raw data and actionable insights, providing e-commerce retailers with the tools they need to stay competitive in an ever-changing marketplace.

At the core of our system lies a sophisticated data collection mechanism powered by Selenium WebDriver. This automation enables real-time extraction of product pricing and availability from major e-commerce platforms such as Flipkart, Croma, and Reliance Digital. By continuously updating our dataset, we ensure that retailers have access to the most current market trends, allowing them to adapt their pricing strategies proactively. This dynamic approach mitigates the risks of outdated pricing models and enhances decision-making efficiency.

Data preprocessing and analysis form another crucial pillar of our project. The raw data collected undergoes a thorough transformation process that includes cleaning, normalization, and advanced regression analysis techniques. By structuring and refining this information, we can identify optimal pricing points with high accuracy. This analytical rigor allows e-commerce businesses to make informed, data-backed pricing decisions that maximize both revenue and customer engagement.

Our user interface, developed using Streamlit, plays an equally significant role in making our solution accessible and interactive. Users can effortlessly input product details, retrieve real-time pricing comparisons, and visualize trends through dynamic graphs and tables. The incorporation of natural language processing (NLP) adds an additional layer of accessibility by enabling clear, voice-based responses. This feature is particularly beneficial for users who prefer auditory feedback, enhancing the inclusivity of our system.

Ensuring the robustness and reliability of our project has been a top priority. We implemented a comprehensive testing framework using the unittest module, rigorously assessing our system under various conditions. By simulating diverse scenarios and handling potential exceptions, we have fortified our solution against common errors and system failures. This meticulous testing process guarantees that our tool operates seamlessly in real-world applications, providing users with a dependable and high-performance experience.

Beyond its technical capabilities, our project underscores the broader impact of integrating machine learning and artificial intelligence into business operations. The ability to automate and optimize pricing strategies has far-reaching implications, enabling retailers to respond dynamically to market fluctuations, competitor pricing, and consumer demand. This adaptive approach not only drives profitability but also fosters a more efficient and data-informed e-commerce ecosystem.

While our current system represents a significant step forward, we recognize that innovation is a continuous journey. Looking ahead, we envision expanding our project by incorporating more sophisticated machine learning models, integrating a wider range of data sources, and enhancing user engagement through AI-driven insights. These advancements will further solidify our system as a powerful tool for strategic pricing in the digital marketplace.
Reflecting on our journey from conceptualization to implementation, we have gained invaluable knowledge, tackled complex challenges, and refined our technical expertise. The lessons learned have strengthened our ability to build practical, real-world solutions that address pressing industry needs. This experience has also reinforced our belief in the transformative potential of technology when applied with creativity, precision, and a user-centric approach.

In conclusion, our project is not merely an endpoint but a stepping stone toward greater technological advancements in e-commerce. It highlights the importance of collaboration, adaptability, and continuous learning in solving real-world business challenges. As we move forward, we remain committed to pushing the boundaries of what is possible, exploring new frontiers in data analytics, and inspiring future innovations in the field. Our hope is that this project serves as a catalyst for further research and development, driving the evolution of smarter, more efficient, and data-driven pricing strategies in online retail.

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9. Appendix

9.1. Appendix-A
Project Repository Details

Project Title: Regression Analysis Based Pricing Recommendations for E- commerce Retailers

Batch: A13

Batch Members:
1. Bandiboyina Jahnavi (21B01A0517)
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Department: Computer Science and Engineering

Institution: Shri Vishnu Engineering College for Women

Guide: Mr. V. Rajesh Babu

Submission Date: [03/04/2025]

Project Repository Link
The complete project files, including source code, documentation, and additional resources, are available at the following GitHub repository:

GitHub Repository: https://github.com/spoorthiGoteti/Regression-analysis-based-pricing-Recommendations-for-E-Commerce-Retailers/

For quick access, scan the QR code below:

9.2 Appendix B

9.2.1 Introduction to Python

Python is a high-level, interpreted programming language known for its simplicity and versatility. It is widely used in data science, web development, automation, and artificial intelligence. Its ease of learning and extensive libraries make it one of the most popular languages in the world.

Benefits of Python

- **Cross-platform compatibility**: Runs on Windows, macOS, and Linux.
- **Open-source and free**: No licensing costs.
- **Large community support**: Extensive forums, tutorials, and resources available.
- **Integration capabilities**: Can be integrated with other languages such as C, C++, and Java.
- **Automation**: Helps in automating repetitive tasks with ease.
- **Rich library ecosystem**: Offers specialized libraries for various domains, including AI, web development, and data analysis.
- **Scalability**: Suitable for both small and large-scale applications.

Features of Python

- **Dynamic Typing**: No need to declare variable types explicitly.
- **Interpreted Language**: Executes code line-by-line, making debugging easier.
- **Object-Oriented and Functional Programming Support**: Allows both paradigms.
- **Extensive Standard Library**: Includes modules for regular expressions, file I/O, networking, and more.
- **Memory Management**: Automatic garbage collection.
- **High-Level Language**: Simple syntax that is close to human language.
- **Embeddable and Extensible**: Can be embedded in other languages or extended with C/C++.
- **Multi-threading and Multiprocessing**: Supports concurrent execution.
- **Rich GUI Support**: Libraries like Tkinter, PyQt, and Kivy help build desktop applications.

Python's simplicity, combined with its rich ecosystem of libraries like Scikit-learn, Streamlit, and Plotly, makes it an ideal language for various applications, including machine learning, web development, and data visualization. Its ease of learning ensures that both beginners and experts can leverage its capabilities effectively, making it a dominant force in modern programming.

9.2.2. Introduction to Streamlit

Streamlit is an open-source Python library that enables the rapid development of interactive web applications for data visualization, automation, and machine learning. It simplifies the process by eliminating the need for front-end development, allowing users to create fully functional applications using only Python scripts.

Streamlit integrates seamlessly with data science libraries such as Pandas, NumPy, Plotly, and Scikit-learn, making it a preferred choice for data-driven applications.

Key Features of Streamlit

- **Ease of Use:** Requires minimal coding and automatically generates an interface.
- **Interactive Widgets**: Supports elements like sliders, buttons, and dropdowns for user interaction.
- **Real-time Data Updates:** Enables efficient data refreshing using caching mechanisms.
- **Seamless Integration:** Works with popular Python libraries for data analysis and visualization.
- **Easy Deployment:** Can be deployed on cloud platforms with minimal configuration.

Benefits of Using Stream

- **Fast Development**: Reduces development time by eliminating the need for manual UI design.
- **Enhanced User Interaction:** Allows real-time data manipulation and visualization.
- **Lightweight and Efficient:** Runs directly from a Python script without complex setup.
- **Scalability:** Can handle small-scale projects as well as large analytical applications.
- **Open-Source and Free:** No licensing costs, making it accessible to all developers.

This project leverages Streamlit to build an interactive data analysis and visualization dashboard that enables users to explore and compare various data points efficiently. Users can input queries through a simple interface, and data is dynamically fetched and processed for real-time analysis. Sidebar widgets allow filtering based on specific parameters, ensuring a smooth and customized experience. Streamlit’s caching mechanisms optimize performance, preventing unnecessary re-computation. The platform integrates interactive charts and graphs to visualize trends and insights effectively.

Various visualization techniques enhance user understanding, providing an intuitive representation of data patterns. These insights help users make informed decisions, with recommendations generated based on analyzed trends.

Streamlit plays a crucial role in simplifying the development of this project by providing an intuitive and efficient platform for data exploration and visualization. Its ability to create interactive applications without extensive coding makes it an excellent tool for analytical and data-driven solutions. By leveraging Streamlit's capabilities, this project successfully demonstrates how real-time data analysis, visualization, and decision support can be effectively implemented in a user-friendly manner.

9.2.3. Introduction to Scikit-Learn

Scikit-Learn is one of the most popular machine learning libraries in Python, offering a powerful and efficient suite of tools for data mining and predictive analytics. Developed as part of the SciPy ecosystem, it provides a simple and consistent interface for implementing a wide range of machine learning algorithms, making it an essential library for data scientists, engineers, and researchers. Built on foundational Python libraries such as NumPy, SciPy, and Matplotlib, Scikit-Learn is designed for ease of use while maintaining high performance. Its modular architecture enables seamless integration with other data processing tools, allowing users to implement everything from basic machine learning models to complex workflows involving feature engineering, hyperparameter tuning, and model validation.

The library is widely used in real-world applications, including finance, healthcare, marketing, image recognition, and natural language processing (NLP). With its rich collection of supervised and unsupervised learning algorithms, Scikit-Learn makes it easy to develop scalable and interpretable machine learning solutions.

Beyond algorithmic support, Scikit-Learn includes robust utilities for data preprocessing, feature selection, model evaluation, and hyperparameter optimization. Its extensive documentation, strong community support, and compatibility with deep learning frameworks like TensorFlow and PyTorch make it a go-to choice for machine learning practitioners.

Key Features of Scikit-Learn

- **Comprehensive Machine Learning Toolkit**: Supports classification, regression, clustering, and dimensionality reduction.
- **Efficient Preprocessing Tools**: Provides functions for feature scaling, normalization, encoding, and transformation.
- **Model Selection and Evaluation**: Includes cross-validation, hyperparameter tuning, and multiple scoring metrics.
- **Pipeline Integration**: Enables seamless execution of preprocessing, transformation, and model training in a single workflow.
- **Extensive Documentation and Community Support**: Offers well-maintained guides, examples, and a large user base for troubleshooting.

Benefits of Using Scikit-Learn

- **User-Friendly API**: Intuitive and consistent syntax simplifies model implementation.
- **Performance and Scalability**: Optimized algorithms ensure efficient execution on large datasets.
- **Interoperability:** Seamlessly integrates with other Python libraries like Pandas, NumPy, and Matplotlib.
- **Reproducibility:** Standardized methods and parameter tuning enable consistent results.
- **Broad Algorithm Support**: Covers traditional machine learning models, including Linear Regression, Decision Trees, Support Vector Machines (SVM), Random Forest, and Gradient Boosting.

Scikit-Learn is utilized in this project to build a machine learning pipeline for predictive modeling. The dataset is first preprocessed, handling missing values and scaling features for better performance. Label encoding is applied where necessary, and polynomial feature transformations enhance feature interactions. The dataset is then split into training and testing sets, ensuring reliable model evaluation.

A variety of machine learning models, including Linear Regression, Decision Trees, Random Forest, Gradient Boosting, Support Vector Regression (SVR) are trained and compared using cross-validation. Hyperparameter tuning is performed through GridSearchCV and RandomizedSearchCV, optimizing model performance by selecting the best combination of parameters. The most effective model is chosen based on evaluation metrics such as R^2 score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

Scikit-Learn's pipeline capabilities ensure a streamlined workflow, where data transformations, scaling, and model training are applied consistently across different models. This automation minimizes human intervention while maximizing efficiency and accuracy. The final trained model provides valuable predictions and insights, demonstrating Scikit-Learn's ability to develop robust, scalable, and high-performance machine learning solutions.

9.2.4. Introduction to Plotly

Plotly is a powerful, open-source graphing library that enables the creation of interactive and visually appealing visualizations in Python. It is widely used for data analysis, business intelligence, and machine learning applications due to its seamless integration with Jupyter notebooks, web frameworks, and dashboards. Unlike static visualization libraries such as Matplotlib, Plotly offers highly interactive charts with features like zooming, panning, hover effects, and dynamic updates.

It supports a broad range of visualization types, including scatter plots, bar charts, histograms, line charts, heatmaps, 3D plots, and geographic maps. Plotly is built on D3.js, WebGL, and JSON for high-performance rendering in web-based applications. It provides compatibility with Dash, a Python framework for building analytical web applications, making it an essential tool for creating interactive data-driven applications. From financial analytics and scientific research to AI-driven dashboards and real-time monitoring systems, Plotly is used across industries to create dynamic visual representations of complex datasets.

Key Features of Plotly

- **Interactive Graphs** : Zooming, hovering, and real-time updates enhance user engagement.
- **Wide Range of Chart Types**: Supports scatter plots, line charts, histograms, heatmaps, 3D plots, and more.
- **Seamless Web Integration**: Generates interactive HTML-based plots for embedding in dashboards and web applications.
- **Customization & Theming**: Offers extensive styling options for colors, labels, tooltips, and animations.
- **High Performance with WebGL**: Enables efficient rendering of large datasets.
- **Integration with Python Libraries**: Works with Pandas, NumPy, Scikit-Learn, and Streamlit.

Benefits of Using Plotly

- **Enhanced User Experience:** Interactive charts provide a more intuitive way to explore data.
- **Scalability:** Optimized for large datasets with WebGL rendering.
- **Web Compatibility**: Easily embeds in web apps, reports, and dashboards.

- **Customization:** Highly flexible styling and annotation options.
- **Real-Time Data Visualization:** Supports live updates for time-sensitive applications.

Plotly is used in this project to create interactive visualizations for price analysis. The dataset is preprocessed to ensure numerical values for plotting, and then various visualizations are generated. A scatter plot is created to show the distribution of product prices by title, with hover tooltips displaying additional product details such as ratings and sources. A bar chart histogram categorizes prices into dynamic bins, allowing users to explore product distributions across different retailers. Plotly's color mapping capabilities differentiate sources, while its hover interactivity provides insights into product details without cluttering the visualization. The Streamlit-based dashboard dynamically updates the graphs based on user-selected filters such as price range, rating, and retailer source, ensuring a highly interactive and data-driven experience. By leveraging Plotly, the project offers an engaging way to analyze pricing trends and compare products across different sellers, making it an effective tool for data-driven decision-making and market analysis.