

Title: Smart Inventory Optimization

in Retail Chains

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1. Introduction

In the dynamic landscape of retail, inventory management remains a critical operational challenge. Overstocking leads to increased holding costs and wasted resources, while understocking results in missed sales opportunities and customer dissatisfaction. This project, conducted as part of a summer internship program, addresses this issue through the development of a predictive analytics solution that forecasts product demand across retail store locations.

The primary objective of this project is to leverage machine learning techniques to predict product demand, thereby enabling optimal inventory planning and restocking decisions. By analyzing historical sales, seasonal trends, promotional impacts, and environmental conditions, the model aims to provide actionable insights for inventory optimization.

2. Objectives

- Develop a machine learning model to predict product demand.
Minimize losses from overstocking and understocking.
- Reduce inventory holding costs.
- Enable better decision-making through a user-friendly dashboard.
- Provide accurate restocking suggestions based on external factors (promotion, season, weather).

3. Project Scope

The project covers the entire machine learning pipeline from data analysis and model development to real-time deployment using Streamlit.

Tools and Technologies Used:

- Python, Pandas, NumPy
- scikit-learn, Matplotlib, Seaborn
- Streamlit for dashboard deployment

Key tasks included:

- Data cleaning and preprocessing
- Feature engineering and selection
- Model training and evaluation
- Deployment of a user interface for prediction

4. Dataset Overview

The dataset comprises 76,000 records and 21 columns containing product information, sales data, pricing, promotion indicators, weather conditions, and seasonal attributes. The target variable for prediction is the 'Demand' column.

Key features include:

- Inventory Level
- Units Sold

- Units Ordered
- Price
- Discount
- Promotion
- Competitor Pricing
- Weather and Seasonality Flags
- Temporal Features (Month, Day, Weekday)

5. Methodology

The methodology followed was:

- **Data Cleaning:** Handling null values, date parsing, encoding categorical variables
- **Exploratory Data Analysis (EDA):** Understanding patterns, visualizing relationships (e.g., promotion vs. demand)
Feature Engineering: Extracting new meaningful features (e.g., weekday from date, weather flags)
- **Modeling:** Training different models to predict demand
- **Evaluation:** Using R^2 score and RMSE to compare model accuracy
- **Hyperparameter Tuning:** Grid search with cross-validation to improve model performance
- **Deployment:** Creating a Streamlit-based dashboard for user interaction

6. Model Development

Two regression models were explored:

1. Linear Regression

- Simple and easy to interpret
- Achieved a baseline R^2 of **0.75**

2. Random Forest Regressor

- Captures non-linear relationships
- Handles mixed-type features well
- Final R^2 of **0.86**
- Selected as the best-performing model for deployment

Model training was done with `train_test_split`, and performance was validated using `cross_val_score`.

7. Results & Analysis

Key Findings:

- **Promotion** significantly increases product demand
- **Sunny weather** and **summer season** correlate with higher sales
- **Inventory Level** and **Units Sold** are the most influential features

Model Evaluation:

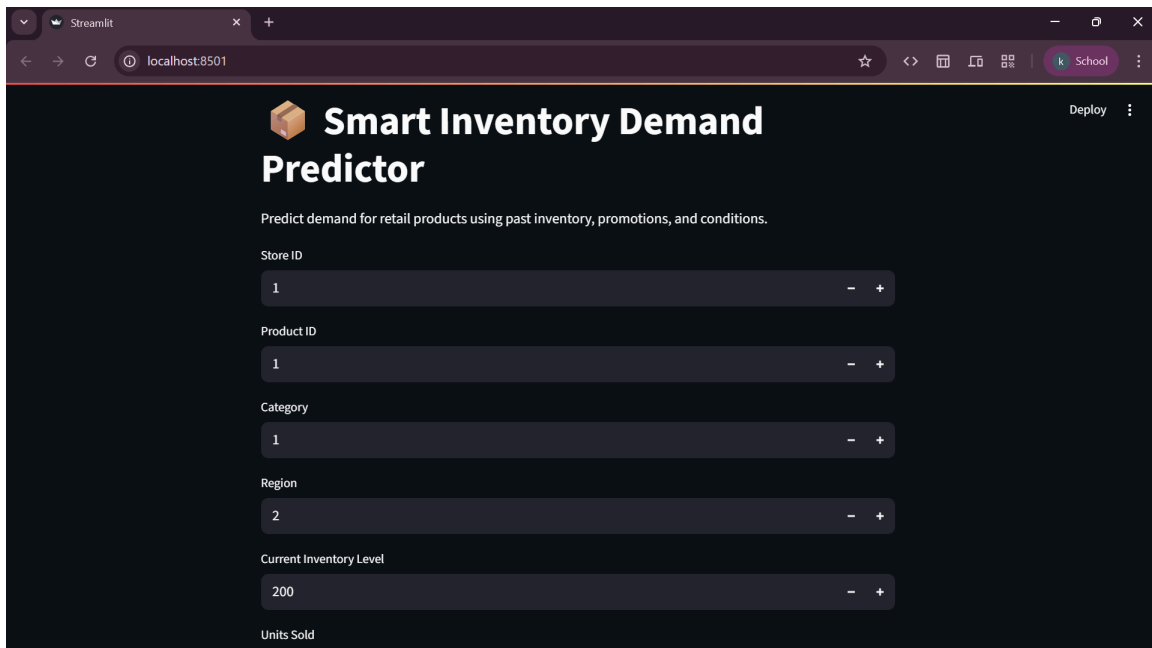
- **Random Forest R^2 Score:** 0.86
- **RMSE:** Low enough to trust forecasts for business use
- **Feature Importance** showed pricing, promotion, and weather among top contributors

8. Dashboard Interface

An interactive **Streamlit dashboard** was developed so users can:

- Input product parameters (price, promotion, inventory, weather, etc.)
- Predict the **expected demand** in real time
- Use a friendly UI suitable for non-technical business users

Example Output:



The screenshot shows a web browser window displaying a Streamlit application titled "Smart Inventory Demand Predictor". The browser's address bar shows "localhost:8501". The application has a dark theme and includes a "Deploy" button in the top right corner. Below the title, a subtitle reads: "Predict demand for retail products using past inventory, promotions, and conditions." The main interface consists of several input fields, each with a label and a numeric value, and a "Units Sold" field at the bottom. The inputs are: Store ID (1), Product ID (1), Category (1), Region (2), and Current Inventory Level (200). Each input field has a minus sign on the left and a plus sign on the right, suggesting a range or increment/decrement functionality.

Input Field	Value
Store ID	1
Product ID	1
Category	1
Region	2
Current Inventory Level	200
Units Sold	

A screenshot of a Streamlit web application running on localhost:8501. The interface features several input controls: 'Units Sold' and 'Units Ordered' are numeric input fields both set to 20; 'Price (₹)' is a numeric input field set to 1.00; 'Discount (%)' is a slider set to 10; 'Promotion Applied?' is a dropdown menu set to 0; 'Competitor Price (₹)' is a numeric input field set to 1.00; and 'Epidemic Active?' is a dropdown menu set to 0. A 'Deploy' button is visible in the top right corner.

A screenshot of the same Streamlit web application, now showing the date and weather selection section. It includes dropdown menus for 'Month' (set to 5), 'Day' (set to 6), and 'Weekday (0=Mon, 6=Sun)' (set to 3). Below these are four radio buttons for weather: 'Sunny' (selected), 'Rainy', 'Snowy', and 'Winter'. A 'Predict Demand' button is located below the weather options. At the bottom, a green box displays the result: 'Predicted Demand: 25 units'.

 Predicted Demand: **25 units**

This app simplifies how decision-makers interact with the AI model and empowers better planning.

9. Conclusion

This project successfully demonstrated the application of machine learning to retail inventory optimization.

By predicting product demand based on historical and contextual data, businesses can:

- Improve restocking efficiency
- Lower inventory-related losses
- Enhance customer satisfaction

The dashboard enables real-time, user-friendly access to insights generated from the predictive model.

10. Future Scope

Future improvements may include:

- Live integration with store databases for real-time forecasting
- Automated replenishment triggers
- Product bundling and category-level predictions
- Cloud-based dashboard hosting for multi-location access
- Adding supplier lead time as an optimization parameter

This system can evolve into a comprehensive demand planning solution for large retail chains.