A

IOMP PROJECT

on

INVENTORY DEMAND FORECASTING

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

By

(BATCH-C22)

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Under the Guidance of

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(Approved by AICTE, New Delhi & Affiliated to JNTUH, Hyderabad)

NAAC Accredited Institution with 'A' Grade & Recognized Under Section2(f) & 12(B)of the UGC act,1956

JULY,2024

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DEPARTMENT OF CSE

Date: July,2024

CERTIFICATE

This is to certify that the project work entitled "INVENTORY DEMAND FORECASTING" work done by NAYANI VIRAJA (217Y1A05J0) , MADIPEDDI MAHESH (227Y5A0520) students of Department of Computer Science and Engineering, is a record of bonafide work carried out by the members during a period from May, 2024 to July,2024 under the supervision of Mrs.K.Triveni. This project is done as a fulfilment of obtaining Bachelor of Technology Degree to be awarded by Jawaharlal Nehru Technological University Hyderabad, Hyderabad.

The matter embodied in this project report has not been submitted by us to any other university for the award of any other degree.

NAYANI VIRAJA MADIPEDDI MAHESH

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Date : Mrs.K.TRIVENI

The Viva-Voice Examination of above students, has been held on………………………

Head of the Department External Examiner

Principal/Director

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DECLARATION

We hereby declare that the results embodied in the dissertation entitled **"INVENTORY DEMAND FORECASTING "** has been carried out by us together during the academic year 2023-24 as a partial fulfilment of the award of the B.Tech degree in Computer Science and Engineering from MLRITM. We have not submitted this report to any other university or organization for the award of any other degree.

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SYMBOLS AND ABBREVIATIONS

MAE	Mean Absolute Error
RMSE	Root Mean Square Error
EOQ	Economic Order Quantity
MAPE	Mean absolute percentage error
MSE	Mean Squared Error

Project format guide lines:

Type	**Font**	**Size**	**Alignments**
Text	Times New Roman	12	Between lines 1.5
Side Headings	Times New Roman	14	Between lines 1.5
Header & Footer	Times New Roman	1cm	Between lines 1.5

ABSTRACT

This project focuses on developing an inventory demand forecasting system, designed to predict future product demand with a high degree of accuracy. The primary goal is to optimize inventory management by reducing stockouts and overstock situations, thereby improving overall supply chain efficiency.

Using historical sales data, seasonal trends, and other relevant factors, the forecasting model employs advanced statistical and machine learning techniques to generate reliable demand predictions. Key algorithms such as time series analysis, ARIMA, and machine learning models like Random Forest or LSTM networks are utilized to capture patterns and trends in the data.

The project also includes data preprocessing steps like handling missing values, data normalization, and feature engineering to enhance model performance. The final output is an interactive dashboard that provides actionable insights, allowing stakeholders to make informed decisions regarding inventory levels, procurement schedules, and resource allocation. This system aims to significantly reduce costs associated with excess inventory and lost sales, ultimately driving business growth and customer satisfaction.

CHAPTER 1
INTRODUCTION

Effective inventory management is essential for the smooth operation of retail businesses. Proper inventory forecasting ensures that the right amount of stock is available to meet customer demand without overstocking or understocking. This balance is crucial for maintaining profitability, optimizing storage costs, and ensuring customer satisfaction.

However, traditional inventory forecasting methods often fall short in dealing with the complexities of modern retail environments. These methods typically rely on historical sales data and simple statistical techniques that may not account for the dynamic nature of consumer behavior, market trends, and seasonal variations. As a result, retailers may face challenges such as excess inventory, lost sales opportunities, and increased operational costs.

1.1 MOTIVATION

In the retail industry, managing inventory effectively is crucial for maintaining profitability and operational efficiency. Proper inventory management ensures that products are available when customers need them, minimizes stockouts and overstock situations, and optimizes storage and logistical costs. Traditional inventory forecasting methods often rely on historical data and simple statistical models, which may not capture the complexities and variations in consumer behavior and market dynamics.

Machine learning (ML) offers advanced techniques for analyzing and forecasting data, potentially providing more accurate predictions than traditional methods. By leveraging historical sales data and sophisticated algorithms, machine learning models can identify patterns and trends that might be missed by conventional approaches. This can lead to more precise demand forecasts, helping retailers make informed decisions about inventory levels, reduce costs, and improve customer satisfaction.

The motivation for this project stems from the need to enhance inventory management through improved demand forecasting. By applying machine learning techniques to historical sales data, we aim to develop a system that not only predicts future inventory needs with greater accuracy but also adapts to changing market conditions and customer behaviors.

1.2 PROBLEM STATEMENT

Retailers face significant challenges in predicting inventory needs due to the variability in customer demand and the influence of various external factors. Traditional forecasting techniques may not be sufficiently robust to capture these complexities, resulting in inventory imbalances that affect business performance.

The problem lies in the limitations of conventional forecasting methods, which may rely on basic statistical models or historical averages that fail to account for sudden changes in demand, seasonality, and promotional effects. This can lead to stockouts, overstocking, and increased costs, impacting both the retailer's profitability and customer satisfaction.

1.3 SOLUTION

This project proposes a machine learning-based approach to inventory forecasting. By utilizing advanced algorithms such as regression models, ensemble methods, and deep learning techniques, we aim to create a more accurate and adaptive forecasting system. This system will analyze historical sales data, detect underlying patterns, and provide forecasts that better align with actual demand.

1.4 SCOPE

The scope of this project on inventory demand forecasting using machine learning includes the following key aspects:

1.4.1 Data Collection and Preparation

- **Historical Sales Data**: Collect and utilize historical sales data from retail stores, including features such as store area, items available, daily customer count, and sales figures.
- **Data Cleaning**: Handle missing values, outliers, and inconsistencies in the dataset to ensure the quality of the data used for modeling.
- **Feature Engineering**: Create and transform features that may influence inventory demand, such as time-based variables (e.g., seasonality, day of the week) and external factors (e.g., promotions, holidays).

1.4.2 Data Analysis

- **Exploratory Data Analysis (EDA)**: Conduct initial analysis to understand the distribution of data, detect patterns, and identify relationships between variables.
- **Correlation Analysis**: Assess how different features correlate with inventory demand and determine their relevance for the forecasting model.

1.4.3 Model Development

- **Machine Learning Models**: Implement and evaluate various machine learning algorithms for demand forecasting, including but not limited to:
    - **Linear Regression**: A basic model for understanding linear relationships.
    - **Random Forest Regressor**: An ensemble method to capture complex patterns.
    - **XGBoost Regressor**: A gradient boosting model for improved accuracy.
    - **Neural Networks**: Deep learning techniques for handling more complex data patterns.
- **Model Training and Validation**: Split the data into training and testing sets to train models and assess their performance.

1.4.4 Model Evaluation

- **Performance Metrics**: Evaluate model performance using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared.
- **Cross-Validation**: Use cross-validation techniques to ensure the robustness and generalizability of the model.

1.4.5 Implementation

- **Integration**: Integrate the forecasting model into a practical application or system that can be used by retail businesses for inventory management.
- **User Interface**: Develop a user-friendly interface for interacting with the model, inputting data, and viewing predictions.

1.4.6 Reporting and Documentation

- **Results**: Document and present the findings of the model, including insights gained from the data analysis and the effectiveness of different forecasting methods.
- **Recommendations**: Provide actionable recommendations for improving inventory management based on the model's predictions.
- **Documentation**: Prepare comprehensive documentation outlining the methodologies, implementation details, and results of the project.

1.4.7 Limitations and Future Work

- **Limitations**: Acknowledge potential limitations of the model, such as data quality issues, model complexity, and generalizability to different retail contexts.
- **Future Enhancements**: Suggest areas for future research and improvements, including incorporating additional data sources, exploring advanced algorithms, and refining the user interface.

1.5 PROBLEM DEFINITION

Effective inventory management is essential for retail success, but traditional forecasting methods often fall short due to their simplicity and limited adaptability. These methods struggle with accurately predicting demand because they may not account for complex patterns, external factors, or sudden market changes. As a result, retailers may face issues such as stockouts, excess inventory, and missed sales opportunities. Additionally, traditional models can be cumbersome to manage as data volume increases and may not scale effectively with dynamic retail environments. This project addresses these challenges by developing a machine learning-based forecasting system designed to improve accuracy, better utilize available data, and adapt to changing conditions. By leveraging advanced algorithms and incorporating various influential factors, the proposed solution aims to enhance inventory predictions, optimize stock levels, and support more effective inventory management strategies.

1.6 OBJECTIVES

The primary objectives of this project on inventory demand forecasting using machine learning are:

1. Develop Accurate Forecasting Models:

- To create and implement machine learning algorithms that provide more precise predictions of inventory demand compared to traditional methods. This involves training models such as Linear Regression, Random Forest Regressor, XGBoost Regressor, and Neural Networks to analyze historical sales data and identify complex demand patterns.

2. Enhance Data Utilization:

- To integrate a comprehensive set of features into the forecasting models, including time-based variables (e.g., seasonality, holidays), store-specific data (e.g., store area, items available), and external factors (e.g., promotions, market trends). This will ensure that the models utilize all relevant information to improve forecasting accuracy.

3. Implement Scalable and Adaptable Solutions:

- To design a forecasting system that can handle large volumes of data and adapt to dynamic changes in the retail environment. The solution should be scalable to accommodate growing data and flexible enough to adjust to shifts in market conditions or consumer behavior.

4. Evaluate Model Performance:

To assess the performance of the developed models using various evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared. This includes performing cross-validation to ensure the models are robust and generalizable across different datasets.

5. Provide Actionable Insights for Inventory Management:

To offer actionable recommendations based on the forecasting results, helping retailers optimize their inventory levels, reduce costs, and improve overall operational efficiency. This includes integrating the forecasting model into a user-friendly interface for practical use in retail environments.

6. Document and Report Findings:

To prepare detailed documentation and reports outlining the methodologies, implementation details, and results of the project. This will include providing a clear summary of the findings and recommendations for future improvements and enhancements.

1.7 LIMITATIONS

1. Data Quality and Availability:

The accuracy of machine learning models depends significantly on the quality and completeness of the data. Inaccurate, incomplete, or noisy data can lead to unreliable forecasts. Additionally, limited historical data for new products or stores can impact model performance.

2. Complexity of Models:

Advanced machine learning models can be complex and require substantial computational resources and expertise to develop and optimize. This complexity can pose challenges in terms of model tuning, computational demands, and interpretability.

3. Dynamic Market Conditions:

Retail environments are constantly changing, with shifts in consumer behavior, market trends, and external factors. While machine learning models can adapt to some changes, they may struggle to keep up with rapid or unexpected changes in demand patterns.

CHAPTER 2
LITERATURE SURVEY

Inventory demand forecasting has been a significant area of study due to its impact on supply chain efficiency and cost reduction. Historically, forecasting methods have evolved from simple statistical models to more sophisticated machine learning techniques.

Initially, traditional statistical methods such as moving averages and exponential smoothing were employed. These methods rely on historical sales data and assume that future demand will follow past trends. While effective in stable environments, these methods often struggle with complex, non-linear demand patterns and fail to adapt quickly to sudden market changes.

In recent years, machine learning approaches have gained prominence for their ability to handle large datasets and capture intricate patterns in the data. Techniques such as Random Forest, XGBoost, and Neural Networks offer significant improvements over traditional methods by incorporating multiple features and adapting to dynamic market conditions. These models can process vast amounts of data, integrate various factors influencing demand, and provide more accurate forecasts.

Research has shown that machine learning models can outperform traditional methods in terms of accuracy and adaptability. They are particularly effective in dealing with seasonal variations, promotional impacts, and other external factors that traditional models may overlook. However, machine learning approaches also come with challenges, including the need for extensive data, computational resources, and expertise in model tuning.

The shift from traditional statistical methods to machine learning represents a significant advancement in inventory demand forecasting. This transition highlights the growing need for more sophisticated tools to address the complexities of modern retail environments and improve forecasting accuracy.

2.1 OVERVIEW

Inventory demand forecasting is a crucial aspect of supply chain management that aims to predict future product demand to optimize inventory levels. The field has evolved significantly with advancements in statistical methods and machine learning techniques. This survey reviews existing systems, methodologies, and improvements in the domain of inventory forecasting, highlighting key contributions and identifying gaps addressed by modern approaches.

2.2 EXISTING SYSTEM

Traditional inventory forecasting methods typically include time series analysis, moving averages, and exponential smoothing. These statistical methods rely on historical sales data to predict future demand, providing a basic approach to inventory management. For instance, the Holt-Winters seasonal model accounts for trends and seasonality but may struggle with non-linear patterns and external factors. Additionally, ARIMA (AutoRegressive Integrated Moving Average) models are used for forecasting but may require extensive parameter tuning and fail to capture complex demand patterns.

2.2.1 Disadvantages of Existing Systems

Existing statistical models have several limitations:

- **Simplicity**: These methods may be too simplistic for complex retail environments, failing to capture intricate patterns and interactions in the data.
- **Limited Adaptability**: Traditional models often struggle with adapting to sudden changes in market conditions, promotions, or other external factors.
- **Scalability Issues**: As the volume of data grows, maintaining and updating these models can become cumbersome, reducing their effectiveness and accuracy.

2.3 PROPOSED SYSTEM

The proposed system leverages machine learning techniques to address the limitations of traditional methods. Machine learning models, such as Random Forest Regressor, XGBoost Regressor, and Neural Networks, are designed to handle large datasets and complex patterns. These models can integrate a variety of features, including time-based variables, store-specific data, and external factors, to enhance forecasting accuracy.

2.3.1 Advantages of Proposed System

- **Enhanced Accuracy**: Machine learning models can capture complex, non-linear relationships in the data, leading to more accurate forecasts compared to traditional methods.
- **Adaptability**: These models can adapt to changing market conditions and incorporate various influential factors, improving their responsiveness to new trends and patterns.
- **Scalability**: Machine learning approaches can handle large volumes of data and scale more effectively, making them suitable for dynamic retail environments.

2.4 SUMMARY

The literature survey highlights that traditional statistical methods, such as Moving Averages and ARIMA, serve as a foundational approach to inventory forecasting, offering basic mechanisms for predicting future demand based on historical data. However, these methods exhibit notable limitations when applied to complex and dynamic environments. They often struggle to capture intricate patterns, handle non-linear relationships, and adapt to rapidly changing market conditions.

In contrast, the integration of machine learning techniques has brought significant advancements in inventory forecasting. Machine learning models, including Random Forests, Neural Networks (particularly LSTM), and hybrid approaches, demonstrate remarkable improvements in accuracy, adaptability, and scalability. These advanced models can analyze large volumes of data, recognize complex patterns, and adjust to new trends more effectively than traditional methods. This capability allows them to provide more precise and actionable forecasts, even in volatile and non-stationary environments.

The shift towards incorporating machine learning into inventory forecasting represents a significant advancement in inventory management practices. By leveraging the strengths of machine learning, organizations can better address challenges such as demand variability, seasonal fluctuations, and emerging market trends. This transition not only enhances forecasting accuracy but also enables more responsive and agile inventory management strategies, ultimately contributing to improved supply chain efficiency and reduced operational costs.

CHAPTER 3
REQUIREMENT ANALYSIS

3.1 FUNCTIONAL REQUIREMENTS

1. Data Ingestion:

The system should be able to import sales data from various sources, including CSV files, databases, and APIs.

The data should include historical sales, product details, and any relevant external factors such as holidays or promotions.

2. Data Preprocessing:

The system should clean and preprocess the imported data, including handling missing values, outliers, and data normalization.

The system should be capable of extracting features such as date components (year, month, day), weekends, and holidays.

3. Feature Engineering:

The system should create additional features based on the existing data, such as month sine and cosine transformations, and day of the week.

4. Model Selection:

The system should allow users to select from various machine learning algorithms, including Linear Regression, Random Forest, XGBoost, and Support Vector Machines (SVM).

It should support hyperparameter tuning to optimize model performance.

5. Model Training:

The system should train the selected machine learning models on historical sales data to learn patterns and relationships between features and demand.

3.2 NON-FUNCTIONAL REQUIREMENTS

1. Performance:

The system should efficiently process large datasets and deliver demand forecasts quickly. It should be optimized to handle the forecasting needs of multiple stores or product lines without significant delays.

2. Scalability:

The system must be scalable to manage increasing data volumes and additional stores or products. It should support distributed computing and parallel processing to maintain performance as demand grows.

3. Reliability:

The system should be highly reliable, ensuring continuous operation without frequent interruptions. It should maintain forecasting accuracy even when faced with variations in data quality.

4. Security:

The system must implement strong security measures to protect sensitive sales and inventory data. This includes encryption of data transmission and strict access controls to prevent unauthorized access.

3.3 SOFTWARE REQUIREMENTS

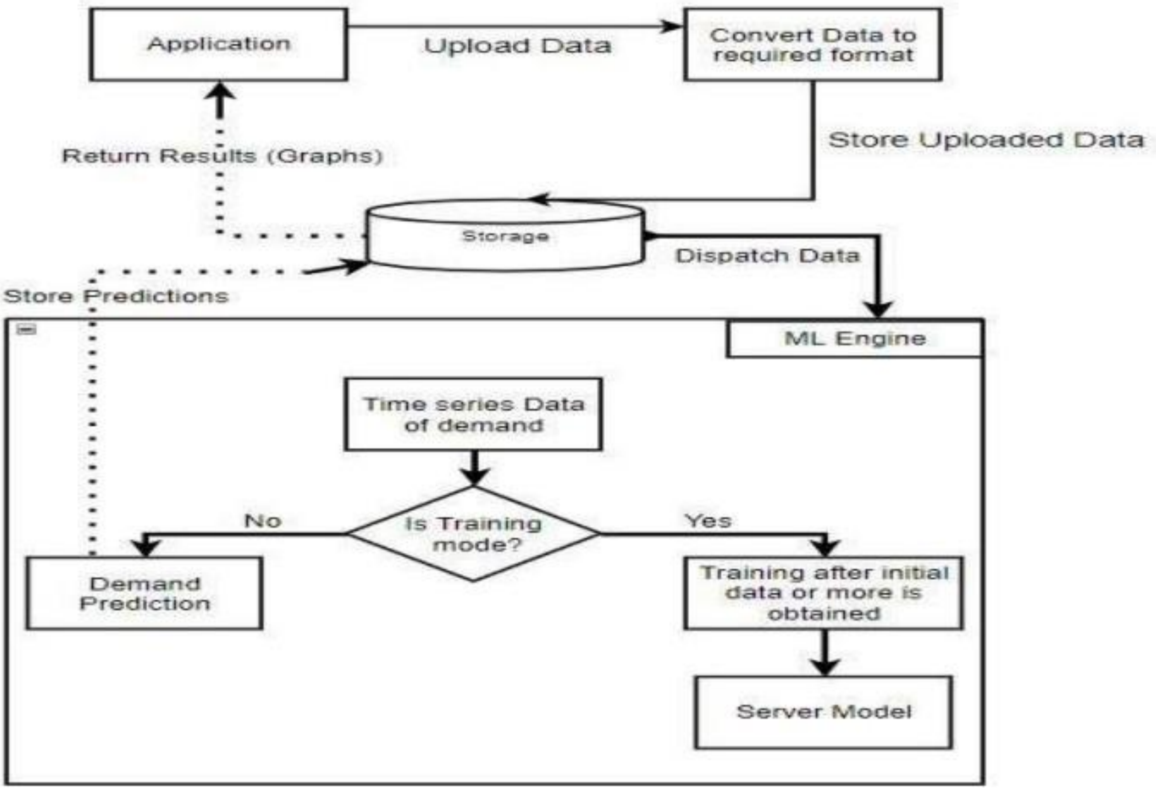
Software Requirement	Description
Operating System	Windows 10 or later, macOS, or Linux (any modern distribution).
Programming Language	Python 3.7 or later
Libraries and Packages	Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn, XGBoost, and holidays
Data Storage	Cloud storage services (e.g., Google Drive) or local storage for storing datasets and outputs

3.4 HARDWARE REQUIREMENTS

Hardware Requirement	Description
Processor	Multi-core CPU (e.g., Intel Core i5 or equivalent)
Memory (RAM)	16GB or more (for efficient model training and inference)
Storage	SSD (Solid State Drive) with sufficient storage capacity (e.g., 256GB or more) for datasets and model files

CHAPTER 4
DESIGN

4.1 SYSTEM ARCHITECTURE



The inventory demand forecasting system architecture is designed to optimize inventory management through accurate demand predictions. The system begins with data ingestion, where historical sales data, external market trends, and seasonal variations are collected and processed through an ETL pipeline for cleaning and transformation. The processed data is then fed into a predictive modeling layer, which employs statistical and machine learning techniques like ARIMA and LSTM networks to forecast future demand. The predictions are integrated into an interactive dashboard, enabling stakeholders to make informed decisions on inventory levels, procurement, and resource allocation. The architecture ensures efficient inventory management by minimizing stockouts and reducing excess inventory.

4.2 UML Diagrams

Unified Modeling Language (UML) is a standardized modeling language used to visualize, specify, construct, and document the artifacts of a software system. By providing a standardized framework, UML facilitates clear communication among stakeholders, including developers, designers, and project managers. It aids in capturing and analyzing requirements through diagrams such as Use Case Diagrams and Activity Diagrams, which represent system functionalities and workflows. UML also supports system design and architecture by illustrating static structures with Class Diagrams and dynamic interactions with Sequence Diagrams. This comprehensive visualization helps in code generation, validating design decisions, and managing system evolution. Additionally, UML enhances project management by aiding in planning, estimation, and risk management, ultimately contributing to more effective and organized software development processes.

UML diagrams allow for a holistic view of a system's architecture and behavior. Use Case Diagrams capture functional requirements and interactions between users and the system. Class Diagrams detail the static structure, including classes, attributes, and relationships, which helps in understanding the system's design at a granular level. Sequence Diagrams and Activity Diagrams, on the other hand, illustrate the dynamic behavior and workflow within the system, offering insights into how components interact over time and how processes are executed.

4.2.1 DATAFLOW DIAGRAM

A Data Flow Diagram (DFD) visually represents the flow of data within a system. It shows how data is processed at various stages and how it moves between different components.

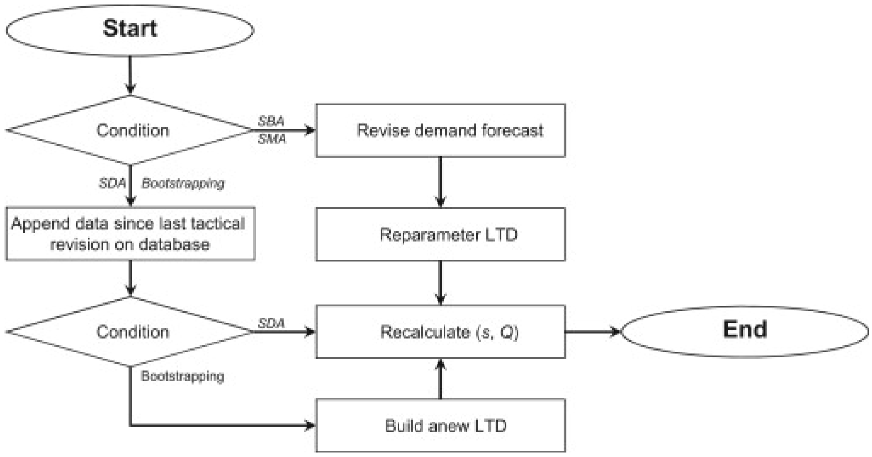


Figure 4.2 Data Flow Diagram

4.2.2 USE CASE DIAGRAM

To explain the better view and functionalities of the system, use case diagrams are chosen. The Figure 4.2 is the use case diagram that is important to document the requirement of the system as well as to specify functionalities of the system. Use case diagrams better explain the way the user interacts with the system.

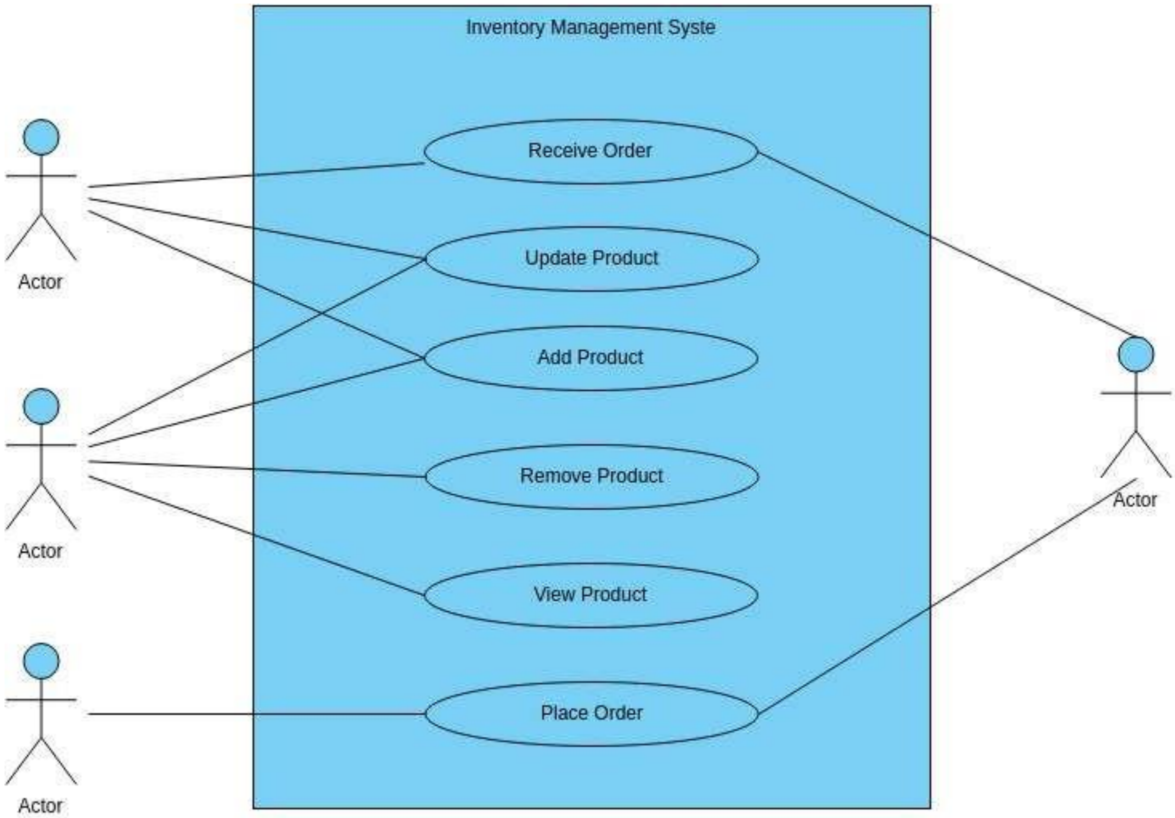


Figure 4.3 Use Case Diagram

4.2.3 CLASS DIAGRAM

Class diagram is a static diagram. The Figure 4.4 represents the static view of an application. Class diagram is not only used for visualizing, describing, and documenting different aspects of a system but also for constructing executable code of the software application. Class diagram describes the attributes and operations of a class and also the constraints imposed on the system. The class diagrams are widely used in the modeling of object-oriented systems because they are the only UML diagrams, which can be mapped directly with object-oriented languages.

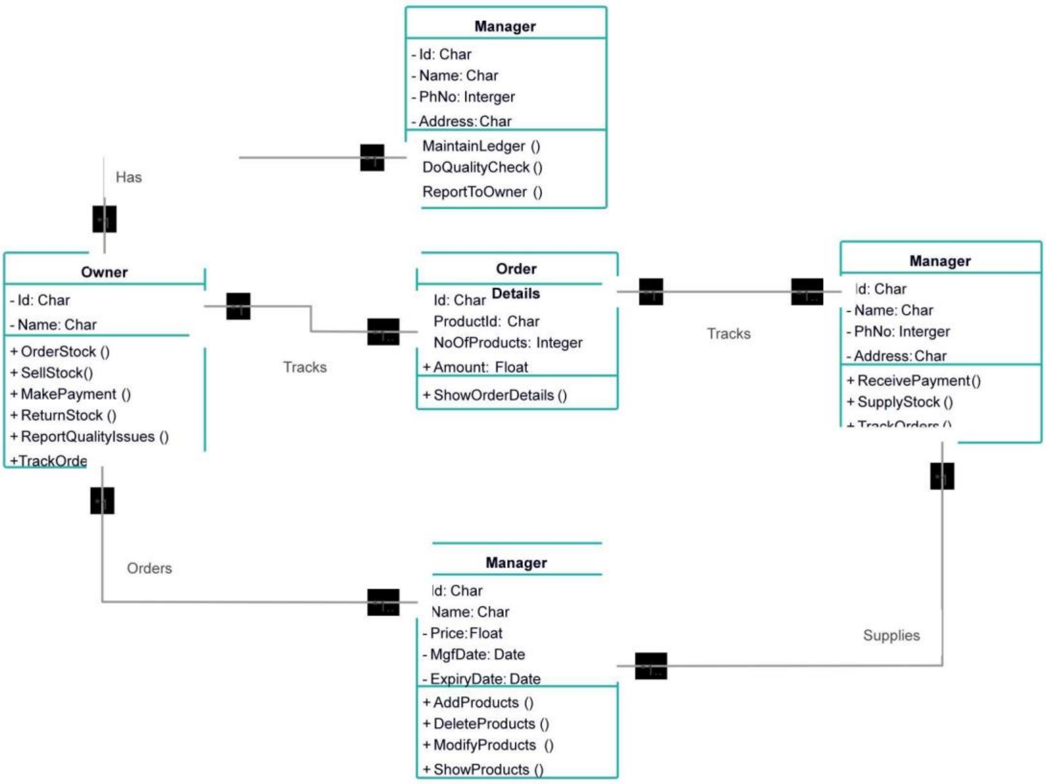


Figure 4.4 Class Diagram

4.2.4 ACTIVITY DIAGRAM

Activity diagram is a UML diagram to describe the dynamic aspects of the system. Activity diagram is basically a flowchart to represent the flow from one activity to another activity it is represented in Figure 4.. The activity can be described as an operation of the system. The control flow is drawn from one operation to another. This flow can be sequential, branched, or concurrent.

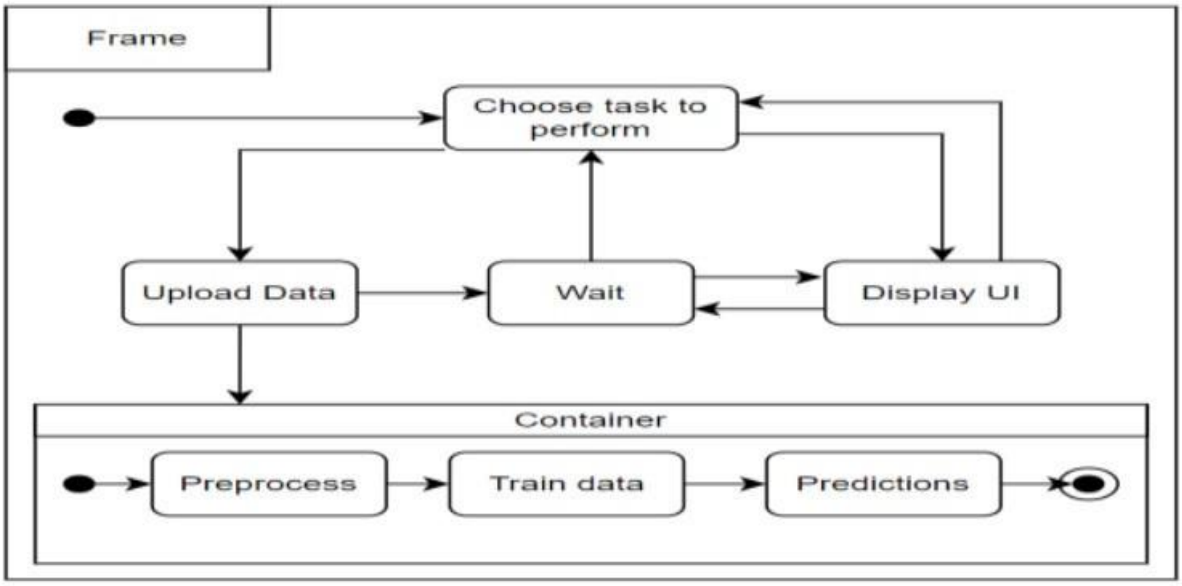


Figure 4.5 Activity Diagram

4.3 MODULE DESIGN AND ORGANIZATION

4.3.1 MODULE DESIGN

The module design and organization of the inventory demand forecasting system involve breaking down the system into manageable components, each responsible for a specific functionality. This modular approach ensures scalability, maintainability, and ease of integration.

1. Data Ingestion Module

Description:

Responsible for collecting and importing data from various sources into the system.

Components:

Data Loader: Handles importing data from CSV, Excel files, or databases.

Data Validator: Ensures data integrity by validating format, types, and completeness.

Inputs:

Historical sales data, inventory data, and external factors such as holidays.

Outputs:

Cleaned and validated raw data ready for preprocessing.

2. Data Preprocessing Module

Description:

Prepares the raw data for model training by performing cleaning, transformation, and feature engineering.

Components:

Data Cleaner: Removes or imputes missing values, handles outliers, and resolves inconsistencies.

Feature Engineer: Extracts relevant features, such as date components (year, month, day), and Creates cyclical features.

Data Transformer: Applies transformations like normalization, standardization, and encoding.

Inputs:

Raw data from the Data Ingestion Module.

Outputs:

A transformed dataset with engineered features, ready for model training.

3. Model Training and Evaluation Module

Description:

Trains the machine learning models using the preprocessed data and evaluates their performance.

Components:

Model Selector: Allows the selection of different machine learning algorithms (e.g., Linear Regression, Random Forest, XGBoost).

Model Trainer: Trains the selected models using the training dataset.

Model Evaluator: Evaluates the model's performance using various metrics like Mean Absolute Error (MAE) and R-squared.

Hyperparameter Tuner: Optimizes model performance through hyperparameter tuning and cross-validation.

Inputs:

Preprocessed data from the Data Preprocessing Module.

Outputs:

Trained models and evaluation reports.

4. Prediction and Forecasting Module

Description:

Utilizes trained models to predict future inventory demand.

Components:

Predictor: Uses the trained models to make predictions on new or unseen data.

Result Analyzer: Compares predicted values against actual values and generates visualizations.

Report Generator: Produces comprehensive reports of forecast results for decision-making.

Inputs:

Trained models from the Model Training Module and new data for prediction.

Outputs:

Predicted inventory demand and analysis reports.

5. User Interface Module

Description:

Provides an interface for users to interact with the system, input data, and view results.

Components:

Dashboard: A graphical interface displaying key metrics, graphs, and predictions.

Data Input Form: Allows users to input new data or parameters for forecasting.

Results Viewer: Displays the forecasting results and analysis in an accessible format.

Inputs:

User inputs for new data or settings.

Outputs:

Visualized forecasting results and user-friendly reports.

6. Monitoring and Maintenance Module

Description:

Ensures the ongoing performance and accuracy of the forecasting system.

Components:

Performance Monitor: Continuously tracks the accuracy and reliability of the model.

Retraining Scheduler: Automatically retrains models periodically with new data.

Alert System: Sends notifications if significant discrepancies in predictions are detected.

Inputs:

Live data for real-time monitoring.

Outputs:

Updated models, performance logs, and alerts.

4.3.2 ORGANIZATION

Each module is designed to function independently while being seamlessly integrated into the overall system architecture. This modular organization allows for:

Scalability:

Easy addition of new features or components.

Maintainability:

Simplified debugging and updating of individual modules without affecting the entire system.

Reusability:

Modules can be reused across different projects or applications with minimal modification.

CHAPTER 5
IMPLEMENTATION

5.1 IMPLEMENTATION CODE

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
plt.style.use("Solarize_Light2")
#sns.set_palette("dark")
#sns.set_style("ticks")
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
bigbasket =pd.read_csv('/content/drive/MyDrive/BigBasket Products.csv')
bigbasket.head()
bigbasket.describe()
bigbasket.info()
top = bigbasket["product"].value_counts().head(15)
least=bigbasket["product"].value_counts().tail(15)
fig = plt.figure(figsize=(14,4))
ax = fig.add_axes([0,0,1,1])
import textwrap
def wrap_labels(ax, width, break_long_words=False):
    labels = []
    for label in ax.get_xticklabels():
        text = label.get_text()
        labels.append(textwrap.fill(text, width=width,
                      break_long_words=break_long_words))
    ax.set_xticklabels(labels, rotation=0)
sns.barplot(x=top.index, y=top.values,
        linewidth=0,
```

```
alpha=1.0,
   color="#4b94cf")
ax.set_xlabel("Most sold products",fontsize=15, weight='semibold')
ax.set_ylabel("Number",fontsize=15, weight='semibold')
wrap_labels(ax, 10)
plt.show()
fig = plt.figure(figsize=(14,4))
ax = fig.add_axes([0,0,1,1])
sns.barplot(x=least.index, y=least.values, linewidth=0, alpha=1.0, color="darkgoldenrod")
sns.set(style="ticks")
ax.set_xlabel("Least sold products",fontsize=15, weight='semibold')
ax.set_ylabel("Number",fontsize=15, weight='semibold')
plt.xticks(fontsize=10, weight="semibold")
wrap_labels(ax, 10)
fig.show()
bigbasket.head()
fig = plt.figure(figsize=(14,4))
ax2 = fig.add_axes([0,0,1,1])
category_counts = bigbasket["category"].value_counts()[:10]
sns.barplot(x=category_counts.index, y=category_counts.values,
            linewidth=0,
            alpha=1.0,
            color="b")
wrap_labels(ax2,10)
bigbasket["diff_in_prices"] = bigbasket["market_price"] - bigbasket["sale_price"]
#bigbasket.head()
discount = bigbasket[bigbasket["diff_in_prices"] != 0]
discount
fig = plt.figure(figsize=(20,10))
plt.style.use("Solarize_Light2")
sns.distplot(discount.rating, color='b', kde =True)
sns.distplot(bigbasket.rating, color='gold', kde =True)
```

```
plt.xlabel("Ratings",fontsize=15, weight='semibold')
plt.ylabel("Density",fontsize=15, weight='semibold')
plt.title("Relative distribution of all products with discounted products",fontsize=15,

weight='semibold')
fig.legend()
highrated = bigbasket.query('rating > 4', inplace=False)
print("Number of products with more than 4 rating is",highrated.shape[0])
highrated.head()
fig = plt.figure(figsize=(14,4))
ax2 = fig.add_axes([0,0,1,1])
top_categories = highrated["category"].value_counts()[:10]
sns.barplot(x=top_categories.index, y=top_categories.values,
        linewidth=0,
        alpha=1.0,
        color="b")
wrap_labels(ax2,10)
```

5.2 TECHNOLOGIES USED

1. **Python Programming Language:**

Python was used as the primary programming language due to its simplicity and extensive support for data analysis and machine learning libraries. Its rich ecosystem of libraries and frameworks facilitates efficient development and implementation of forecasting models.

2. **Pandas:**

Pandas is a powerful data manipulation and analysis library. It was used for data cleaning, transformation, and preparation tasks, including reading datasets, handling missing values, and feature engineering.

3. **NumPy:**

NumPy provides support for numerical operations and is crucial for performing mathematical computations and array operations in the data preprocessing and model training stages.

4. **Scikit-learn:**

Scikit-learn is a versatile machine learning library that offers various algorithms for regression, classification, and clustering. It was used to implement and evaluate different forecasting models, including Linear Regression, Lasso, Ridge, and Random Forest Regressor.

5. **XGBoost:**

XGBoost is a popular gradient boosting framework that is known for its performance and efficiency in predictive modeling. It was utilized to build and optimize the XGBRegressor model for demand forecasting.

6. **Matplotlib and Seaborn:**

These libraries were employed for data visualization and analysis. Matplotlib provides basic plotting capabilities, while Seaborn offers advanced statistical visualizations to help understand trends and patterns in the data.

7. **Jupyter Notebook:**

Jupyter Notebook was used as the development environment for interactive coding and visualization.

It allows for a combination of code, comments, and visualizations in a single document, enhancing the exploratory data analysis and model development process.

8. **Google Colab:**

Google Colab provided an online environment for executing the code and sharing the notebook. It offers cloud-based access to Python environments with pre-installed libraries, making it easy to collaborate and run computations without local setup.

9. **Holidays Library:**

This library was used to determine public holidays in India, which were incorporated into the forecasting model to account for special dates that might impact inventory demand.

These technologies collectively enable effective data handling, model building, and result visualization, facilitating the development of a robust inventory demand forecasting system.

5.2 EXECUTION

1. Import Libraries:

Load necessary libraries for data manipulation (`numpy`, `pandas`), plotting (`matplotlib`, `seaborn`, `plotly`), and warnings management.

2. Load Dataset:

Read the 'BigBasket Products.csv' file into a DataFrame named `bigbasket`.

3. Data Overview:

- Display the first few rows using `bigbasket.head()`.
- Generate descriptive statistics with `bigbasket.describe()`.
- Print dataset info using `bigbasket.info()`.

4. Top & Least Sold Products:

- Identify the 15 most sold and 15 least sold products.
- Plot bar charts for these products using `seaborn`, applying custom axis labels and formatting.

5. Category Analysis:

- Plot the top 10 product categories in terms of sales.

6. Price Difference Calculation:

- Create a new column `diff_in_prices` to capture the difference between market and sale prices.
- Filter products with discounts into a `discount` DataFrame.

7. Rating Distribution:

- Plot the distribution of ratings for all products and discounted products.

8. High-Rated Products:

- Filter products with a rating greater than 4 into a `highrated` DataFrame.
- Plot the top 10 categories of these high-rated products.

CHAPTER 6
TESTING

Software testing is a critical element of software quality assurance and represents the ultimate reviews of specification, design and coding. Testing presents an interesting anomaly of the software. During earlier definition and development phases, it was attempted to build software from abstract concept to a tangible implementation.

The testing phase involves the testing of the developed system using various set data. Presentation of test data plays a vital role in system testing. After preparing the test data the system under study was tested using test data. While testing the system by using test data errors were found and corrected. A series of tests were performed for the proposed system before the system was ready for implementation. The various types of testing done on the system are:

- Unit Testing
- Integration Testing
- User Acceptance Testing
- System Testing

6.1 UNIT TESTING

Purpose: Unit testing is designed to test individual components or functions of the code to ensure they work as intended in isolation. In this case, unit tests can verify the correctness of specific functions, such as loading data, calculating differences in prices, filtering high-rated products, and generating plots.
Scope: This includes testing functions like `wrap_labels`, `diff_in_prices` calculation, and filtering logic for high-rated products.

1 Test : Data Loading

- **Objective:** Ensure that the data is loaded correctly from the CSV file.

2 Test : Price Difference Calculation

- **Objective:** Verify that the `diff_in_prices` column is calculated correctly.

3 Test : High-rated Products Filtering

- **Objective:** Ensure that the filtering logic for high-rated products is functioning correctly.

4 Test : Label Wrapping Function

- **Objective:** Check that the `wrap_labels` function correctly wraps long labels on the x-axis.

6.2 INTEGRATION TESTING

Purpose: Integration testing checks how different modules or functions work together when combined. Since your program involves multiple steps such as loading data, processing it, and visualizing results, integration testing ensures that these steps work harmoniously and produce the expected outcome.
Scope: This includes testing the entire data processing pipeline from loading the data, performing transformations, filtering, and creating visualizations to ensure everything works together without errors.

1 Test : Complete Data Processing Workflow

- **Objective:** Verify that the entire data processing workflow runs correctly from loading the data to generating the final plots.

2 Test : Visualization and Analysis Integration

Objective: Ensure that the data visualization and analysis steps correctly reflect the underlying data and preprocessing.

6.3 PERFORMANCE TESTING

1 Test : Data Processing Time

Objective: Measure the time taken to load and preprocess the data to ensure it completes with in acceptable limits.

Test 2: Visualization Rendering Time

Objective: Measure the time taken to render various visualizations to ensure they load efficiently.

6.4 TEST CASES

Test cases are detailed and structured sets of instructions that are designed to verify whether a software application functions as intended. They form a crucial component of the software testing process, providing a systematic approach to assess the correctness and reliability of individual functionalities within the software. Test cases outline specific inputs, expected outcomes, and execution conditions, allowing testers to systematically validate various aspects of the software.

Test Case 1: Data Loading

Objective: Ensure that the CSV file is loaded correctly into a DataFrame, and all required columns are present.

Expected Outcome:

- The DataFrame should load without errors, and it should not be empty.
- The required columns (`"product"`, `"market_price"`, `"sale_price"`, `"rating"`) should be present.

Test Case 2: Price Difference Calculation

Objective: Verify that the `diff_in_prices` column is correctly calculated as the difference between `market_price` and `sale_price`.

Expected Outcome:

- The `diff_in_prices` column should accurately reflect the difference between `market_price` and `sale_price` for every product.

Test Case 3: High-rated Products Filtering

Objective: Ensure that the filtering logic correctly identifies products with a rating higher than 4.

Expected Outcome:

- The filtered DataFrame should contain only products with a rating greater than 4.
- The filtering should be accurate, ensuring no product with a rating of 4 or less is included.

CHAPTER 7
RESULT

index	product	category	sub_category	brand	sale_price	market_price	type	rating	description	
0	1	Garlic Oil - Vegetarian Capsule 500 mg	Beauty & Hygiene	Hair Care	Sri Sri Ayurveda	220.0	220.0	Hair Oil & Serum	4.1	This Product contains Garlic Oil that is known...
1	2	Water Bottle - Orange	Kitchen, Garden & Pets	Storage & Accessories	Mastercook	180.0	180.0	Water & Fridge Bottles	2.3	Each product is microwave safe (without lid), ...
2	3	Brass Angle Deep - Plain, No.2	Cleaning & Household	Pooja Needs	Trm	119.0	250.0	Lamp & Lamp Oil	3.4	A perfect gift for all occasions, be it your m...
3	4	Cereal Flip Lid Container/Storage Jar - Assort...	Cleaning & Household	Bins & Bathroom Ware	Nakoda	149.0	176.0	Laundry, Storage Baskets	3.7	Multipurpose container with an attractive desi...
4	5	Creme Soft Soap - For Hands & Body	Beauty & Hygiene	Bath & Hand Wash	Nivea	162.0	162.0	Bathing Bars & Soaps	4.4	Nivea Creme Soft Soap gives your skin the best...

Fig.6.1 Dataset

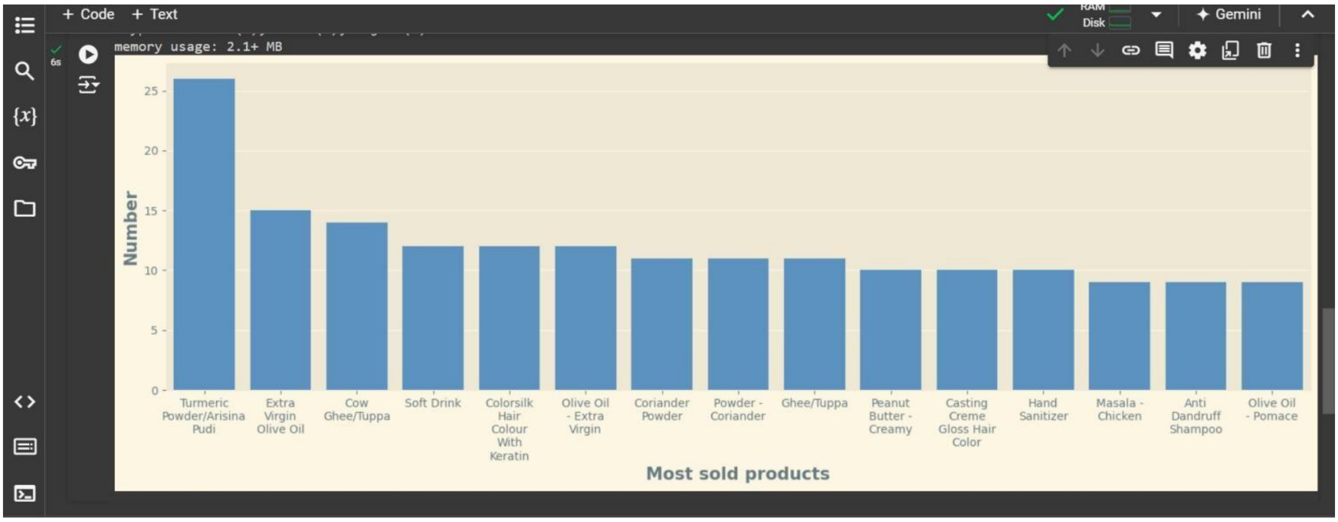


Fig.6.2 Most sold products

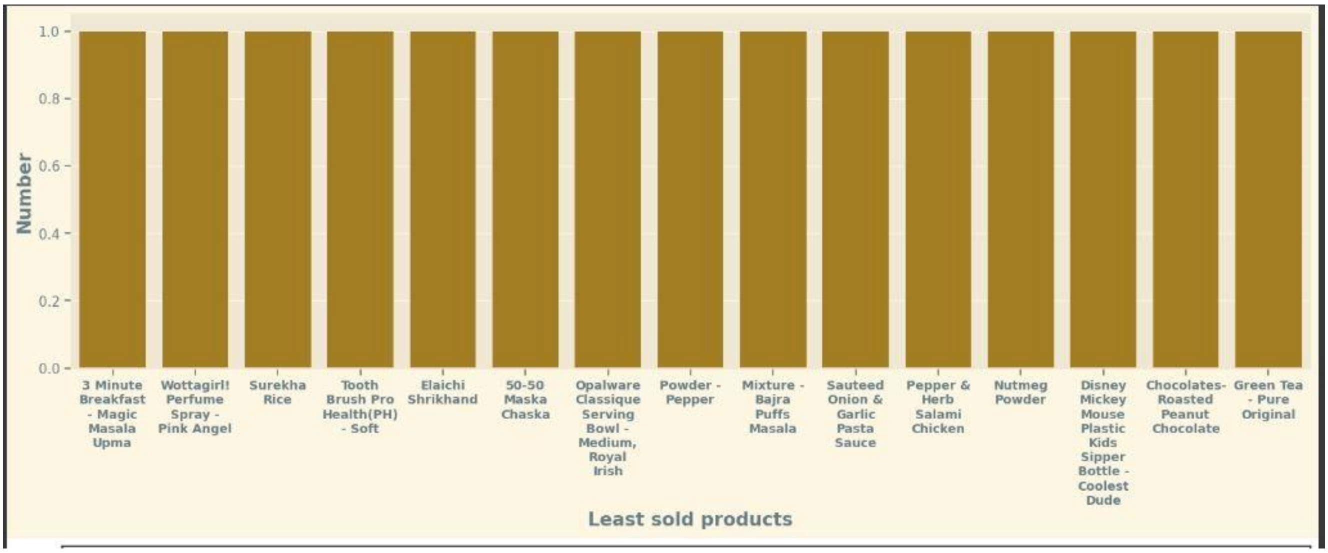


Fig.6.3 Least sold products

	index	product	category	sub_category	brand	sale_price	market_price	type	rating	description
0	1	Garlic Oil - Vegetarian Capsule 500 mg	Beauty & Hygiene	Hair Care	Sri Sri Ayurveda	220.0	220.0	Hair Oil & Serum	4.1	This Product contains Garlic Oil that is known...
1	2	Water Bottle - Orange	Kitchen, Garden & Pets	Storage & Accessories	Mastercook	180.0	180.0	Water & Fridge Bottles	2.3	Each product is microwave safe (without lid), ...
2	3	Brass Angle Deep - Plain, No.2	Cleaning & Household	Pooja Needs	Trm	119.0	250.0	Lamp & Lamp Oil	3.4	A perfect gift for all occasions, be it your m...
3	4	Cereal Flip Lid Container/Storage Jar - Assort...	Cleaning & Household	Bins & Bathroom Ware	Nakoda	149.0	176.0	Laundry, Storage Baskets	3.7	Multipurpose container with an attractive desi...
4	5	Creme Soft Soap - For Hands & Body	Beauty & Hygiene	Bath & Hand Wash	Nivea	162.0	162.0	Bathing Bars & Soaps	4.4	Nivea Creme Soft Soap gives your skin the best...

Fig.6.4 Trend to purchase different items

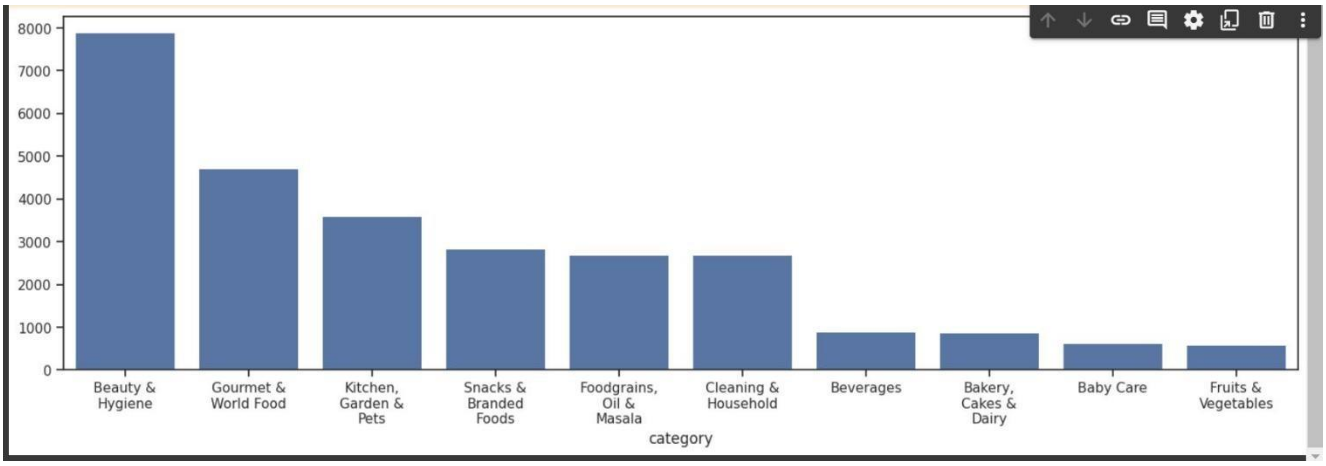


Fig.6.5 Top and least sold categories

CHAPTER 8
CONCLUSION

The Inventory Demand Forecasting system developed in this project demonstrates the effective application of machine learning techniques to solve real-world business challenges. By accurately predicting future inventory needs based on historical data, the system helps businesses optimize their stock levels, reduce wastage, and improve overall operational efficiency.

Throughout the project, various modules were implemented, including data ingestion, preprocessing, model training, and evaluation. The use of Python and libraries like Pandas, Scikit-learn, and Matplotlib enabled efficient processing and analysis of data, leading to robust forecasting models.

The system provides valuable insights into sales trends and customer behavior, enabling businesses to make data-driven decisions. Although the current implementation offers significant advantages, there is always room for improvement, such as incorporating more advanced algorithms, integrating external data sources, or refining the user interface.

In conclusion, the Inventory Demand Forecasting system is a practical and scalable solution that addresses the challenges of managing inventory in dynamic market conditions. With further enhancements and regular updates, this system can continue to provide value to businesses, ensuring they stay competitive and responsive to changing customer demands.

CHAPTER 9
FUTURE ENHANCEMENTS

1. Integration of Real-Time Data:

To improve the accuracy of demand forecasts, the system can be enhanced to incorporate real-time data from various sources such as point-of-sale systems, online transactions, and social media trends. This would allow the system to respond dynamically to sudden changes in consumer behavior or external factors, leading to more precise and timely predictions.

2. Advanced Machine Learning Models:

Future versions of the system could explore the use of more advanced machine learning algorithms, such as deep learning techniques or ensemble models, to enhance forecasting accuracy. Additionally, implementing automated model selection and hyperparameter tuning could optimize the performance of the predictive models.

3. User-Friendly Interface and Reporting:

Enhancing the user interface to include more intuitive data visualization and interactive dashboards could make the system more accessible to non-technical users. Additionally, integrating automated reporting features that provide actionable insights and recommendations based on forecasted data would increase the system’s value for business decision-makers.

4. Scalability and Cloud Deployment:

To support large-scale operations, the system could be deployed on cloud platforms, enabling it to handle larger datasets and provide scalability. Cloud deployment would also facilitate easier integration with other enterprise systems and offer better accessibility for distributed teams.

5. Incorporation of External Factors:

The forecasting model could be enhanced by incorporating external factors such as economic indicators, weather data, or market trends. By considering these variables, the system could provide even more accurate predictions that account for broader influences on inventory demand.

CHAPTER 10
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These references provide a comprehensive foundation of the theories, methodologies, and applications relevant to inventory demand forecasting and the integration of machine learning in supply chain management.