AMAZON SALES FORECASTING AND ANALYSIS:

TRENDS, INSIGHTS, AND PERFORMANCE

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MALLA REDDY UNIVERSITY
(Telangana State Private Universities Act No.13 of 2020 and G.O.Ms.No.14, Higher Education (UE) Department)

CERTIFICATE

This is to certify that this is the Application development lab record entitled "**AMAZON SALES DATA ANLAYSIS**", submitted by **M. SAI RAM (2211CS010379), P.NIKHITHA (2211CS010438), M.VINAY (2211CS010367), G. KISHORE (2211CS010209)** B.Tech III year II semester, Department of CSE during the year 2024-25. The results embodied in this report have not been submitted to any other university or institute for the award of any degree or diploma.

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DECLARATION

I declare that this project report titled **AMAZON SALES DATA ANLAYSIS** submitted in partial fulfillment of the degree of B. Tech in CSE is a record of original work carried out by me under the supervision of **MR.G.RAJU** and has not formed the basis for the award of any other degree or diploma, in this or any other Institution or University. In keeping with the ethical practice in reporting scientific information, due acknowledgements have been made wherever the findings of others have been cited.

Signature

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ABSTRACT

The Amazon Sales Data Analysis project is an interactive dashboard that leverages data visualization and predictive analytics to analyze Amazon sales trends. Developed using Dash, Plotly, Pandas, and Machine Learning algorithms, the application provides insights into revenue, profit, units sold, product performance, and regional sales variations. It integrates predictive modeling to forecast future sales and evaluate model performance using various statistical metrics.

The application preprocesses raw sales data, handling missing values, converting date formats, and structuring numerical fields like total revenue, total cost, profit, and unit price. Users can filter data dynamically by product category and region, gaining customized insights through interactive time-series analysis, revenue distribution, product price trends, and profitability comparisons. Additionally, the dashboard highlights order processing times, cost outliers, and sales patterns based on order priority, helping businesses refine their pricing and logistics strategies.

To enhance predictive analytics, the project employs Machine Learning techniques, including Linear Regression for sales forecasting and revenue prediction. The Lasso and Least Angle Regression (LARS) methods are explored for feature selection and model optimization. Model performance is quantified using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 score, Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE). Kernel Density Estimation (KDE) plots are also utilized to visualize data distributions and model residuals.

The project further compares multiple models using PyCaret, an automated machine learning library, to determine the most effective approach for sales trend prediction and anomaly detection. By integrating real-time data processing, interactive visualizations, and predictive analytics, this project provides data-driven insights to improve sales strategies, enhance profitability, and optimize inventory management in the e-commerce sector.

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CHAPTER - 1

INTRODUCTION

1.1 Introduction

In today's competitive e-commerce landscape, data-driven decision-making is crucial for businesses to maximize revenue and optimize sales strategies. The Amazon Sales Data Analysis project is designed to provide insights into sales trends, revenue distribution, and product performance through interactive visualizations and predictive analytics. This project utilizes Dash, Plotly, Pandas, and Machine Learning (ML) techniques to analyze historical sales data, forecast future trends, and evaluate sales performance across different regions and products.

The primary objective of this project is to help businesses and analysts understand key sales metrics**,** including total revenue, profit margins, units sold, and regional sales patterns**.** By leveraging data preprocessing, visualization, and predictive modeling**,** the project enables users to identify high-performing products, seasonal sales trends, and potential inefficiencies in order processing**.**

To enhance predictive capabilities, the project incorporates Machine Learning algorithms such as Linear Regression, Lasso Regression, and Least Angle Regression (LARS) for sales forecasting and revenue prediction**.** Performance evaluation is conducted using statistical metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 score, Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE)**.** The PyCaret library is also used to compare multiple models and automate predictive analytics.

Additionally, Kernel Density Estimation (KDE) plots are utilized to analyze data distributions, while anomaly detection techniques help identify irregularities in sales data. The dashboard allows users to filter data dynamically based on products and geographical regions**,** providing customized insights through interactive visualizations.

By integrating real-time data processing, advanced visualizations, and predictive analytics**,** this project serves as a valuable tool for business intelligence and decision-making**.** The insights generated can help improve sales strategies, optimize pricing models, forecast demand, and enhance overall operational efficiency in the ecommerce domain.

1.2 Problem Statement

In the highly competitive e-commerce industry, businesses face challenges in understanding sales trends, predicting future revenue, and optimizing sales strategies. With vast amounts of transactional data generated daily, organizations often struggle to extract meaningful insights that can drive decision-making. Amazon, as one of the largest online marketplaces, requires efficient data analysis tools to monitor sales performance, identify profitable products, and forecast demand.

This project aims to address the following key problems:

1. **Lack of Sales Trend Visibility** – Businesses need to track sales patterns, revenue fluctuations, and product performance across different time periods and geographical regions. Without clear insights, they risk making uninformed decisions.

2. **Inaccurate Sales Forecasting** – Traditional reporting methods often fail to predict future sales accurately. The absence of predictive analytics leads to inventory mismanagement, stockouts, or overstocking, impacting profitability.

3. **Difficulty in Identifying High-Performing Products and Regions** – Companies struggle to pinpoint which products contribute most to revenue and which regions generate the highest sales. This lack of insight makes it difficult to allocate resources effectively.

4. **Inability to Detect Anomalies and Outliers** – Unusual sales spikes or drops can indicate market trends, pricing issues, or fraudulent activities. Without an efficient anomaly detection system, businesses may overlook critical risks and opportunities.

5. **Need for an Automated and Scalable Analysis Framework** – Manual data analysis is time-consuming and prone to human errors. Organizations require a real-time, automated dashboard that simplifies data exploration and enhances decision-making through interactive visualizations and predictive modeling.

1.3 Objective of Project

The Amazon Sales Data Analysis project aims to provide an interactive, data-driven solution for analyzing and predicting sales trends. The primary goal is to help businesses extract meaningful insights from historical sales data to enhance decision-making, forecasting, and operational efficiency**.**

The specific objectives of the project are:

1.Analyze Sales Trends – Identify patterns in revenue, profit, and units sold over time to understand fluctuations in Amazon sales performance.

2.Develop an Interactive Dashboard – Create a user-friendly web application using Dash and Plotly to visualize sales data dynamically, allowing users to filter insights based on products and regions**.**

3.Predict Future Sales – Implement Machine Learning models (Linear Regression, Lasso Regression, and Least Angle Regression - LARS) to forecast future revenue and product demand based on historical trends.

4.Evaluate Model Performance – Quantify model accuracy using statistical metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 score, Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE)**.**

5.Compare Multiple ML Models – Utilize PyCaret, an automated machine learning library, to compare different predictive models and determine the most accurate approach for sales forecasting.

6.Detect Anomalies in Sales Data – Identify outliers and irregularities in sales, cost, and order processing using Kernel Density Estimation (KDE) plots and anomaly detection techniques**.**

7.Improve Business Decision-Making – Enable businesses to optimize inventory management, refine pricing strategies, and allocate resources effectively by leveraging data-driven insights.

1.4 Goal of Project

The goal of the Amazon Sales Data Analysis project is to develop an interactive, data-driven dashboard that enables businesses to analyze, visualize, and predict sales trends, revenue patterns, and product performance. By leveraging data analytics and machine learning models, the project aims to help businesses make informed, data-backed decisions to optimize sales strategies, improve revenue forecasting, and enhance overall operational efficiency.

This project focuses on analyzing historical sales data by processing and cleaning raw datasets to extract meaningful insights. It identifies patterns in revenue, profit, and sales trends over time to provide a clear understanding of business performance. The system is designed as a web-based interactive dashboard using Dash and Plotly, allowing users to explore data dynamically by filtering sales records based on product category, region, and time period.

To enhance predictive analytics, the project implements machine learning techniques such as Linear Regression, Lasso Regression, and Least Angle Regression (LARS) to forecast future sales and revenue based on historical trends. Model performance is evaluated using statistical metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 score, Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE). The project also integrates PyCaret, an automated machine learning

library, to compare different models and select the most accurate approach for sales forecasting.

Beyond predictive modeling, the system provides insights to assist in business decision-making by identifying high-performing products, analyzing regional sales variations, and detecting anomalies in revenue trends. These insights help businesses optimize inventory management, refine pricing strategies, and enhance market positioning. By integrating real-time data processing, interactive visualizations, and machine learning-based predictive analytics, this project serves as a valuable tool for businesses seeking to improve profitability, forecast future sales trends, and streamline their overall sales operations in the competitive e-commerce landscape.

CHAPTER 2
PROBLEM IDENTIFICATION

2.1 Existing System

The current approach to Amazon sales data analysis in many businesses relies on manual reporting, basic spreadsheets, and traditional business intelligence tools**.** While these methods provide fundamental insights, they are often time-consuming, inefficient, and lack predictive capabilities**.**

Challenges in the Existing System:

1.Static Reporting & Limited Insights – Many businesses use Excel or simple dashboards that provide historical sales data but lack interactive filtering, real-time updates, or deep analytical insights**.**

2.Lack of Predictive Analytics – Traditional systems rely on descriptive analytics**,** which only analyze past sales trends. Without Machine Learning (ML)-based forecasting**,** businesses struggle to make data-driven future sales predictions.

3.No Automated Model Comparison – Existing systems typically do not automate model selection or performance evaluation**.** Companies manually experiment with models without understanding which one provides the most accurate forecasts.

4.Inefficient Anomaly Detection – Identifying outliers in revenue, order delays, or pricing is difficult with basic tools. Businesses may overlook unexpected spikes, fraudulent activities, or sudden sales drops due to the lack of automated anomaly detection.

5.Limited Interactivity & Customization – Most sales analysis tools do not allow dynamic filtering by product category, region, or sales period**,** making it hard for businesses to explore specific insights efficiently.

6.Scalability Issues – Traditional tools struggle to handle large datasets efficiently, leading to slow processing times and difficulty scaling analysis as data grows over time.

Need for an Improved System

To overcome these limitations, the Amazon Sales Data Analysis project introduces an interactive, machine learning-powered dashboard that enhances sales analysis with:

- **Real-time visualization** of sales trends
- **ML-based sales forecasting** with accuracy evaluation
- **Automated model comparison** using PyCaret
- **Advanced anomaly detection** for fraud and pricing issues
- **Dynamic filtering and interactive exploration** of sales data

This improved system helps businesses save time, enhance forecasting accuracy, and make more informed strategic decisions in the competitive e-commerce industry.

2.2 Proposed System

The Amazon Sales Data Analysis project introduces an advanced, interactive, and machine learning-driven solution to overcome the limitations of existing sales analysis methods. The proposed system integrates data visualization, predictive analytics, and anomaly detection to provide businesses with deeper insights into sales trends, revenue patterns, and product performance**.**

Key Features of the Proposed System:

1.Interactive and Dynamic Sales Analysis

- The system provides an interactive dashboard built with Dash and Plotly**,** allowing users to explore sales trends, revenue distribution, and product-wise performance dynamically.

- Users can filter sales data by region, product category, and date range for customized analysis.

2.Predictive Analytics Using Machine Learning

- The system incorporates Linear Regression, Lasso Regression, and Least Angle Regression (LARS) **to** predict future sales and revenue trends based on historical data.
- Train-test split methodology is used to improve model accuracy.

3.Model Performance Evaluation

- The system quantifies forecasting accuracy using statistical metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 score, Root Mean Squared Logarithmic Error (RMSLE), and Mean Absolute Percentage Error (MAPE)**.**
- The PyCaret library is integrated to automate model comparison**,** ensuring the best-performing model is selected.

4.Anomaly Detection for Sales Data

- Kernel Density Estimation (KDE) plots and other statistical techniques help identify outliers in sales, cost, and order processing times**.**
- Anomalies in revenue trends can indicate fraud detection, pricing errors, or unexpected market changes**.**

5.Automated and Scalable Data Processing

- The system efficiently processes large datasets using Pandas and NumPy**,** ensuring fast computation and scalability**.**
- It automatically cleans data, handles missing values, and standardizes numerical features for better model accuracy.

CHAPTER – 3

REQUIREMENTS

3.1 Software Requirements:

- **Operating System:** Windows 10/11, macOS, or Linux
- **Python Version:** 3.7 or higher

Development Environments:

- **Jupyter Notebook** (for analysis & ML modeling)
- **VS Code**

Python Libraries & Dependencies

✅ **Data Processing & Analysis:**

- pandas – For handling structured data
- numpy – For numerical operations

✅ **Data Visualization:**

- matplotlib – For plotting charts and graphs
- seaborn – For statistical data visualization
- plotly – For interactive dashboards

✅ **Machine Learning & Predictive Analytics**

- Regression Models for Sales Forecasting

  - scikit-learn → Linear Regression, Lasso Regression, Least Angle Regression (LARS)

Model Performance Evaluation Metrics

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- R^2 Score (Coefficient of Determination)
- Root Mean Squared Logarithmic Error (RMSLE)
- Mean Absolute Percentage Error (MAPE)

Automated Model Selection

- pycaret → For comparing multiple ML models and selecting the best one

Dataset Requirements

- **Dataset Format:** .csv (Comma-Separated Values)
- **Dataset Name:** Amazon Sales data.csv
- **Required Columns:**
  - Order Date, Ship Date
  - Total Revenue, Total Cost, Profit, Units Sold, Unit Price
  - Region, Country, Product

3.2 Hardware Requirements:

- **Processor:** Intel Core i3 / AMD Ryzen 3 or equivalent
- **RAM:** 4GB (for basic data processing & visualization)
- **Storage:** 10GB free disk space

CHAPTER – 4
DESIGN AND IMPLEMENTATION

4.1 Design

The design of the Amazon Sales Data Analysis project follows a structured approach that integrates data processing, visualization, and machine learning models into an interactive and user-friendly system. The system architecture consists of three key components: data preprocessing, dashboard development, and machine learning integration.

1.Data Preprocessing

- Load the Amazon Sales data.csv file using Pandas.
- Handle missing values and ensure consistency in numerical fields like Total Revenue, Total Cost, Profit, and Units Sold**.**
- Convert Order Date and Ship Date to datetime format for time-based analysis.
- Extract additional features such as Year, Month, and Processing Time (Ship Date - Order Date)**.**

2.Dashboard Design (Frontend & Visualization)

- Built using Dash and Plotly for an interactive web-based user interface.
- Users can filter data dynamically based on Product Categories, Regions, and Order Dates**.**

- Key Visualizations:

  - **Sales Trends Over Time:** Line chart showing total revenue trends.
  - **Regional Sales Analysis:** Bar chart displaying revenue distribution across different regions.
  - **Country-Wise Revenue Comparison:** Visualization to compare total sales by country.
  - **Profit vs. Units Sold:** Scatter plot showing product-wise profitability.
  - **Unit Price Distribution:** Box plot to analyze product pricing trends.
  - **Order Processing Time Analysis:** Histogram to evaluate delivery efficiency.

3.Machine Learning Integration (Sales Forecasting)

- Implemented **Linear Regression, Lasso Regression, and Least Angle Regression (LARS)** for predicting future sales.
- Split the dataset into **training and testing sets** using the train-test split method.

Evaluated model performance using statistical metrics:

- **Mean Absolute Error (MAE)**
- **Mean Squared Error (MSE)**
- **Root Mean Squared Error (RMSE)**
- **R² Score (Coefficient of Determination)**
- **Root Mean Squared Logarithmic Error (RMSLE)**
- **Mean Absolute Percentage Error (MAPE)**

Used **PyCaret** to compare multiple regression models and select the most accurate one.

4.Anomaly Detection & Statistical Analysis

- Kernel Density Estimation (KDE) used to detect **outliers in sales and pricing data**.
- Identifies **unexpected revenue fluctuations, cost anomalies, and order delays** for business insights.

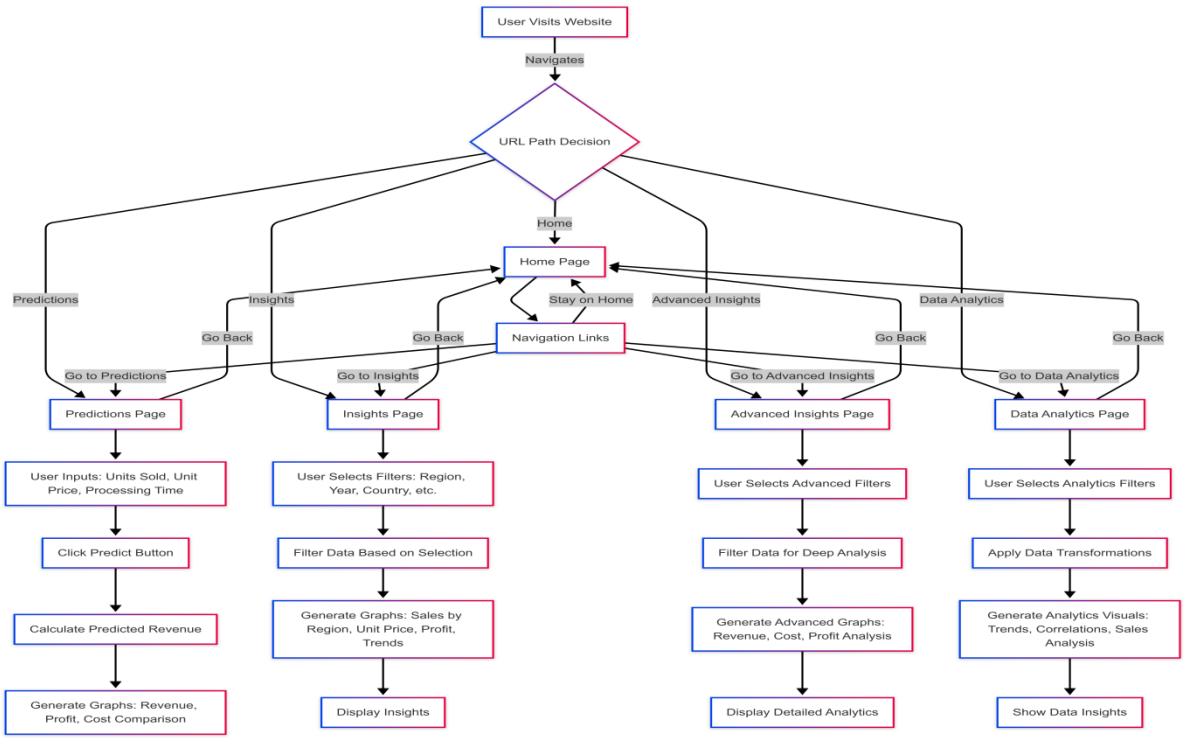

Fig 4.1.1 Flow Chart

4.2 IMPLEMENTATION:

· **Data Preprocessing**

- Format Order Date and Ship Date**.**
- Extract Year, Month, Processing Time**.**
- Handle missing values and standardize Total Revenue, Total Cost, and Profit**.**

· **Dashboard Development**

- Built using Dash and Plotly**.**
- Dropdown filters for selecting products and regions.
- Real-time graph updates based on user input.

· **Machine Learning Integration**

- Models used: Linear Regression, Lasso Regression, and LARS.
- Predicts future sales and revenue trends.
- Evaluated using MAE, MSE, RMSE, and R^2 score**.**
- PyCaret automates model comparison.

· **Visualization & User Interaction**

- Sales Trends Over Time
- Regional & Country-Wise Revenue
- Profit vs. Units Sold
- Unit Price Distribution
- Order Processing Time Analysis

· **Anomaly Detection & Insights**

- Kernel Density Estimation (KDE) detects unusual sales trends.
- Identifies pricing outliers, revenue spikes, and operational inefficiencies**.**

· **Conclusion**

- Dynamic sales dashboard with real-time filtering and ML forecasting**.**
- Helps businesses optimize pricing, inventory, and revenue strategies**.**

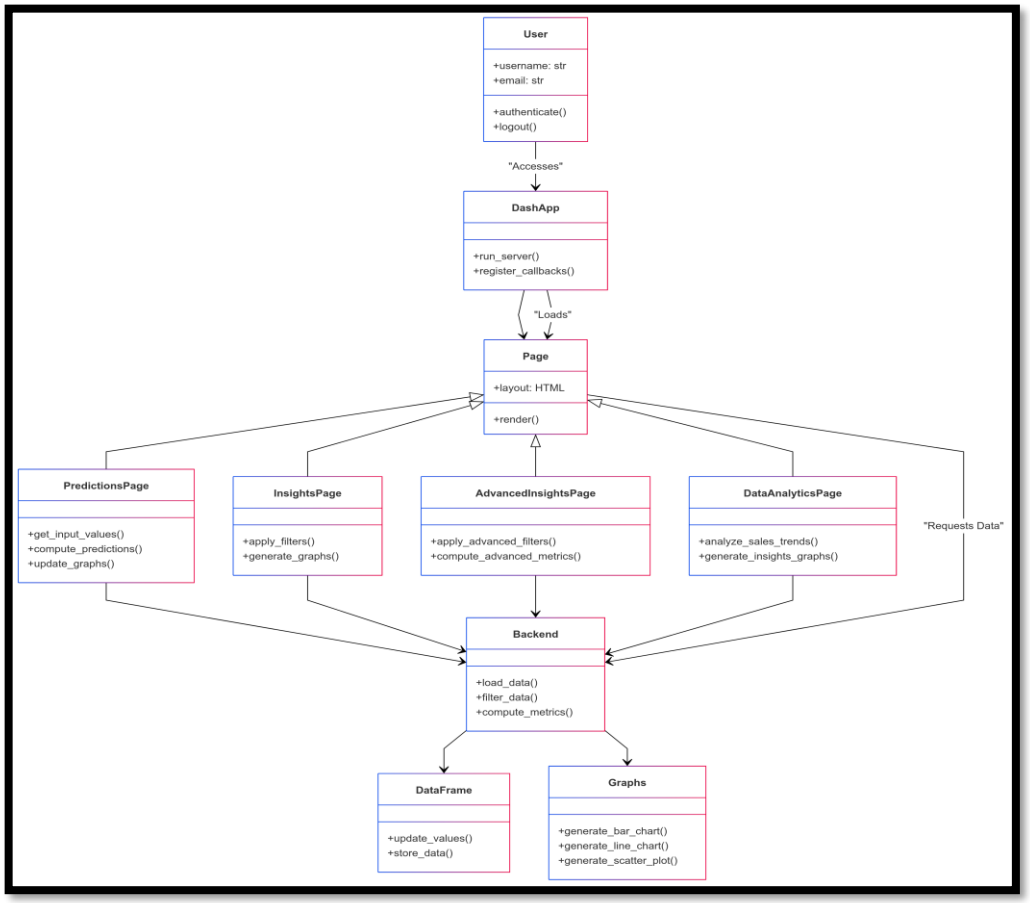

Fig 4.2.1 Class Diagram

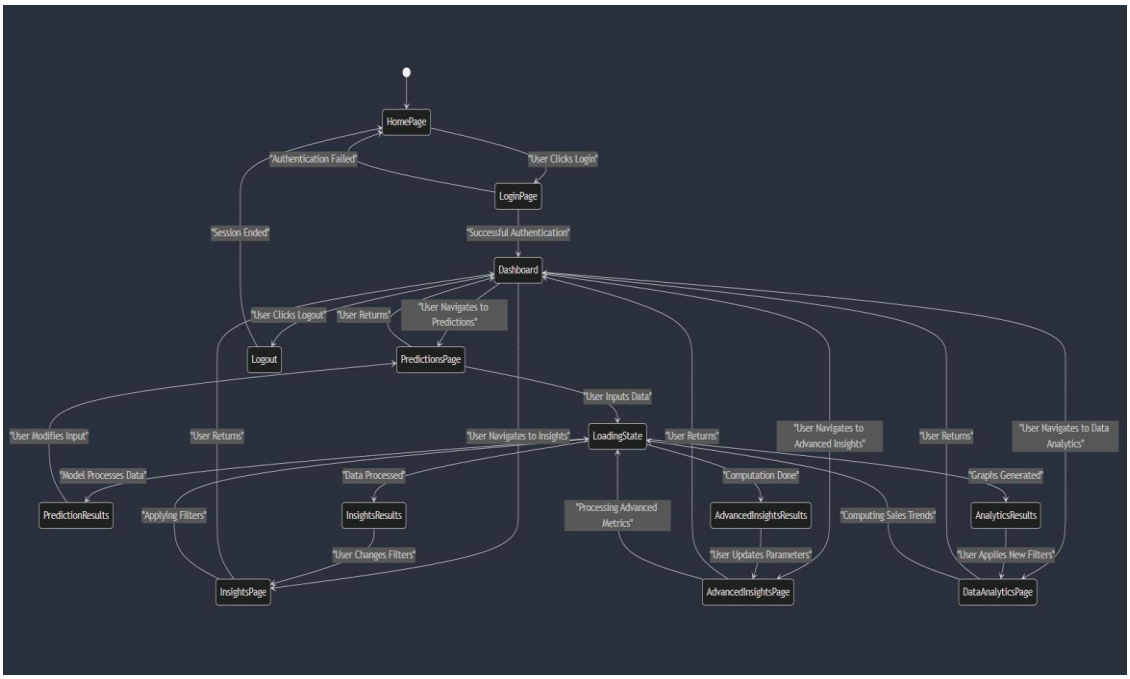

Fig 4.2.2 State Diagram

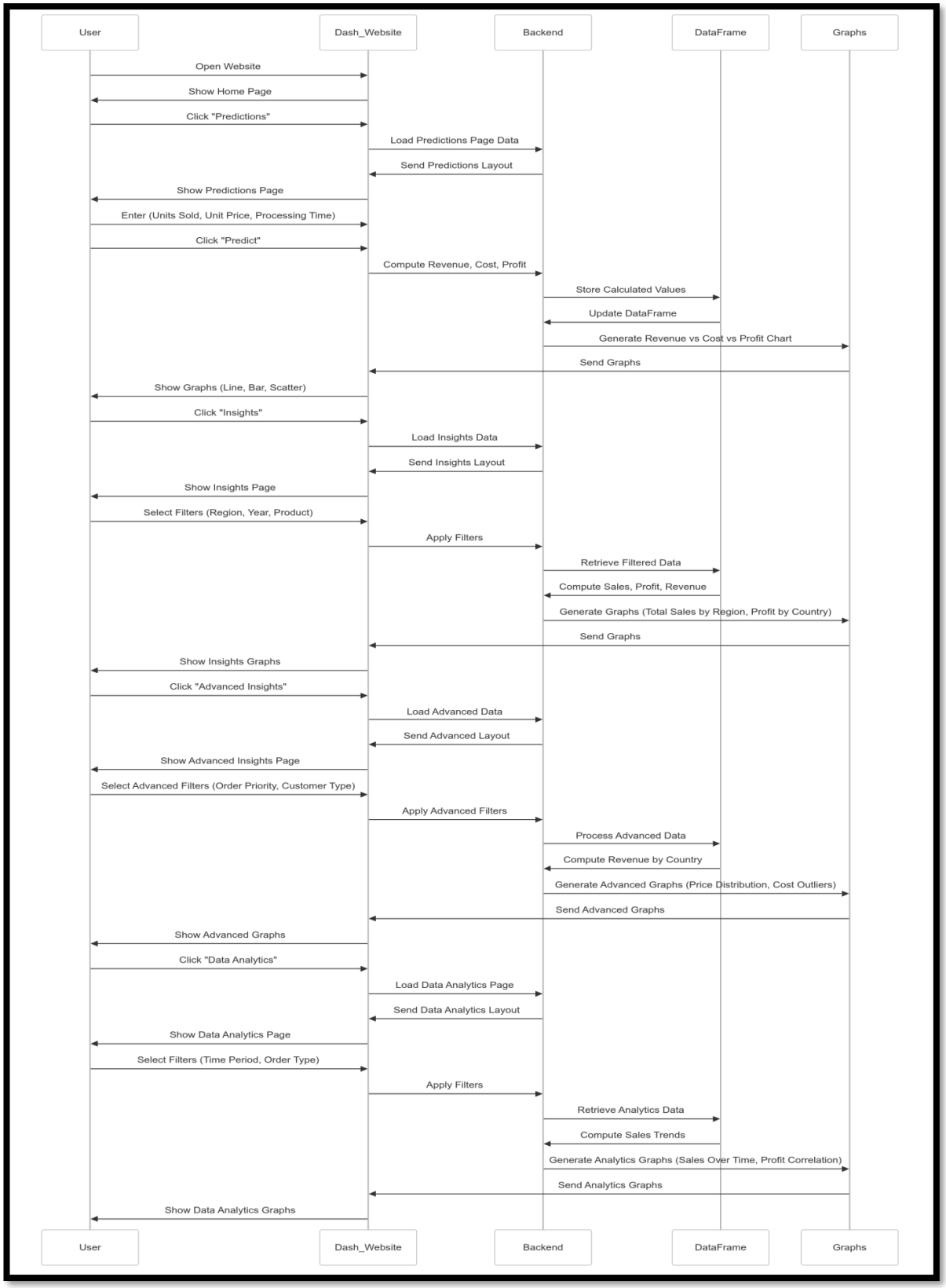

Fig 4.2.3 Sequence Diagram

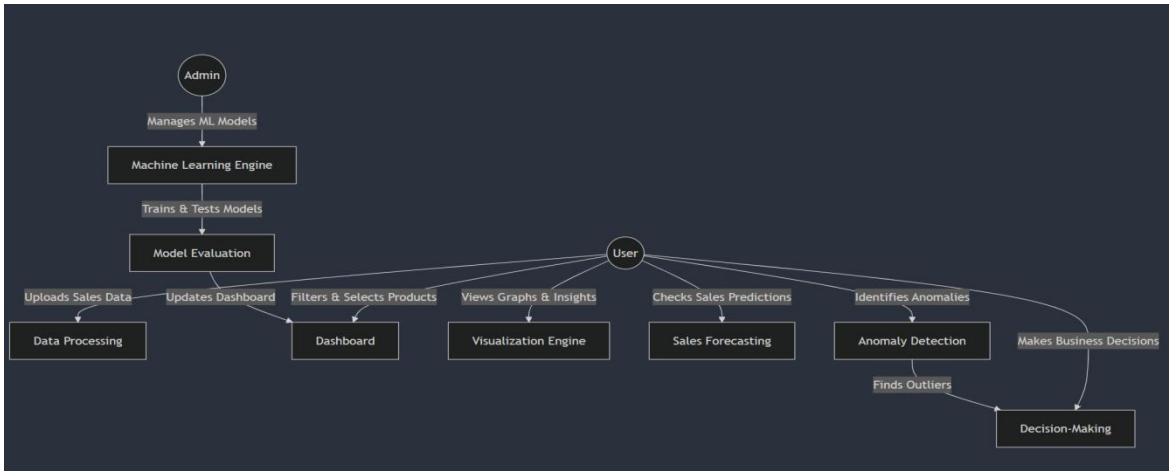

Fig 4.2.4 Use Case Diagram

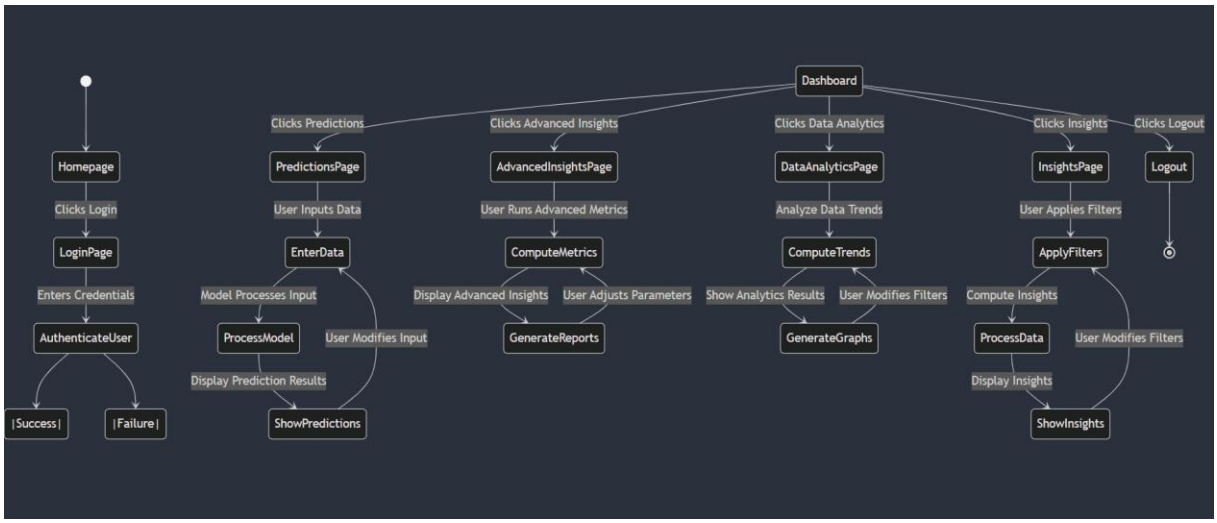

Fig 4.2.5 Activity Diagram

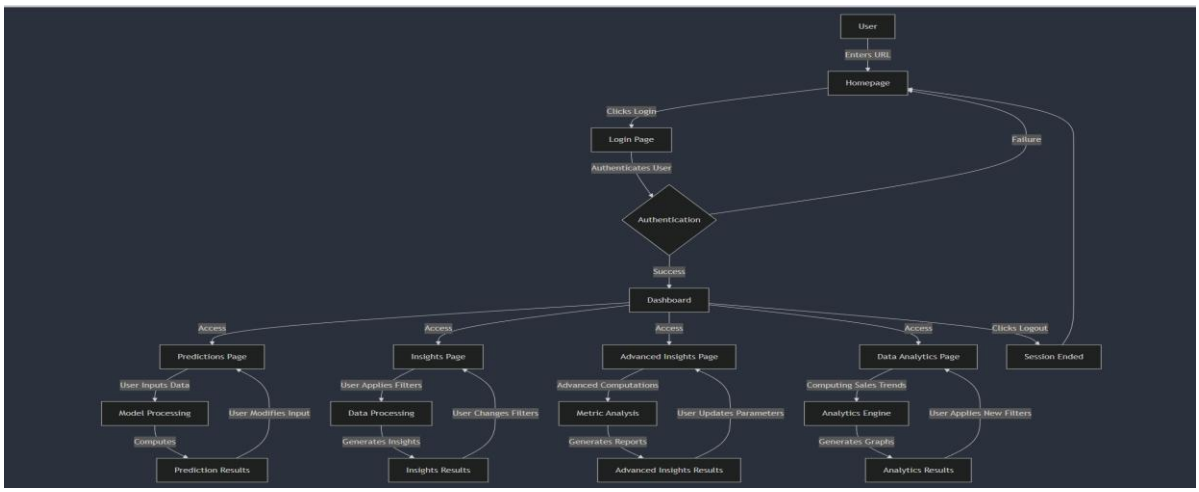

Fig 4.2.6 Block Diagram

CHAPTER – 5

CODE

5.1 Source Code

GitHub Repository Link :

https://github.com/sairam-learner/AmazonSalesData-Analysis

App.js:

```
import dash
from dash import dcc, html, Input, Output, State
import pandas as pd
import plotly.express as px
from dash_extensions.enrich import DashProxy, ServersideOutputTransform
import numpy as np
import dash_bootstrap_components as dbc

# Load and clean data
df = pd.read_csv("Amazon Sales data.csv", encoding='latin-1')
df.columns = df.columns.str.strip()  # Remove extra spaces in column names

# Convert date columns
df['Order Date'] = pd.to_datetime(df['Order Date'], errors='coerce')
df['Ship Date'] = pd.to_datetime(df['Ship Date'], errors='coerce')
df = df.dropna(subset=['Order Date'])

# Add derived columns
df['Year'] = df['Order Date'].dt.year
df['Month'] = df['Order Date'].dt.month_name()
df['Processing Time'] = (df['Ship Date'] - df['Order Date']).dt.days
df['Total Revenue'] = pd.to_numeric(df['Total Revenue'], errors='coerce').fillna(0)
df['Total Cost'] = pd.to_numeric(df['Total Cost'], errors='coerce').fillna(0)
```

```
df['Profit'] = pd.to_numeric(df['Profit'], errors='coerce').fillna(0)
df['Units Sold'] = pd.to_numeric(df['Units Sold'], errors='coerce').fillna(0)
df['Unit Price'] = pd.to_numeric(df['Unit Price'], errors='coerce').fillna(0)

# Initialize Dash app with Bootstrap and suppress callback exceptions
app = DashProxy(__name__, external_stylesheets=[dbc.themes.BOOTSTRAP], transforms=[ServersideOutputTransform()], suppress_callback_exceptions=True)

# Define page layouts
def home_layout():
    return dbc.Container([
        dbc.Row([
            dbc.Col(html.H1("📊 Amazon Sales Forecasting & Analytics: Trends, Insights, and Performance", className="text-center"), width=12)
        ]),
        dbc.Row([
            dbc.Col([
                dbc.Card([
                    dbc.CardHeader(html.H4("Predictions")),
                    dbc.CardBody([
                        html.P("Go to the Predictions page to see revenue predictions."),
                        dcc.Link('Go to Predictions', href='/predictions', className="btn btn-primary")
                    ])
                ], className="mb-3")
            ], width=3),
            dbc.Col([
                dbc.Card([
                    dbc.CardHeader(html.H4("Insights")),
                    dbc.CardBody([
                        html.P("Go to the Insights page to see detailed sales insights."),
                        dcc.Link('Go to Insights', href='/insights', className="btn btn-primary")
                    ])
```

```
            ], className="mb-3")
        ], width=3),
        dbc.Col([
            dbc.Card([
                dbc.CardHeader(html.H4("Trends")),
                dbc.CardBody([
                    html.P("Go to the Advanced Insights page for more detailed analytics."),
                    dcc.Link('Go to Advanced Insights', href='/advanced-insights',
classNamе="btn btn-primary")
                ])
            ], classNamе="mb-3")
        ], width=3),
        dbc.Col([
            dbc.Card([
                dbc.CardHeader(html.H4("ForeCasting")),
                dbc.CardBody([
                    html.P("Go to the Data Analytics page for comprehensive data analysis."),
                    dcc.Link('Go to Data Analytics', href='/data-analytics', classNamе="btn
btn-primary")
                ])
            ], classNamе="mb-3")
        ], width=3)
    ])
], fluid=True)

def predictions_layout():
    return dbc.Container([
        dbc.Row([
            dbc.Col(html.H1("📈 Predicted Revenue", classNamе="text-center"), width=12)
        ]),
        dbc.Row([
            dbc.Col([
```

```
            dcc.Input(id='units-sold', type='number', placeholder='Units Sold', 
className="form-control"),
            dcc.Input(id='unit-price', type='number', placeholder='Unit Price', 
className="form-control mt-2"),
            dcc.Input(id='processing-time', type='number', placeholder='Processing Time', 
className="form-control mt-2"),
            html.Button('Predict Revenue', id='predict-button', n_clicks=0, className="btn 
btn-primary mt-2"),
            html.Div(id='prediction-output', className="mt-3")
        ], width=6)
    ], justify="center"),
    dbc.Row([
        dbc.Col(dcc.Graph(id='predicted-revenue-graph'), width=12)
    ]),
    dbc.Row([
        dbc.Col(dcc.Graph(id='revenue-cost-comparison'), width=6),
        dbc.Col(dcc.Graph(id='profit-graph'), width=6)
    ]),
    dbc.Row([
        dbc.Col(dcc.Graph(id='units-sold-processing-time'), width=6),
        dbc.Col(dcc.Graph(id='unit-price-processing-time'), width=6)
    ]),
    dbc.Row([
        dbc.Col(dcc.Link('Go back to Home', href='/', className="btn btn-secondary mt-
3"), width=12)
    ])
  ], fluid=True)

def insights_layout():
  return dbc.Container([
    dbc.Row([
        dbc.Col(html.H1("🔍 Insights", className="text-center"), width=12)
    ]),
    dbc.Row([
```

```
dbc.Col(dcc.Dropdown(
    id='dropdown1',
    options=[{'label': i, 'value': i} for i in df['Region'].dropna().unique()],
    multi=True,
    placeholder="Select Regions",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown2',
    options=[{'label': i, 'value': i} for i in df['Year'].unique()],
    multi=True,
    placeholder="Select Year",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown3',
    options=[{'label': i, 'value': i} for i in df['Country'].dropna().unique()],
    multi=True,
    placeholder="Select Country",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown4',
    options=[{'label': i, 'value': i} for i in df['Product'].dropna().unique()],
    multi=True,
    placeholder="Select Product",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown5',
    options=[{'label': i, 'value': i} for i in df['Order Priority'].dropna().unique()],
    multi=True,
```

```
        placeholder="Select Order Priority",
        className="mb-3"
    ), width=3),
    dbc.Col(dcc.Dropdown(
        id='dropdown6',
        options=[{'label': i, 'value': i} for i in df['Sales Channel'].dropna().unique()],
        multi=True,
        placeholder="Select Sales Channel",
        className="mb-3"
    ), width=3),
    dbc.Col(dcc.Dropdown(
        id='dropdown7',
        options=[{'label': i, 'value': i} for i in df['Month'].dropna().unique()],
        multi=True,
        placeholder="Select Month",
        className="mb-3"
    ), width=3),
    dbc.Col(dcc.Dropdown(
        id='dropdown8',
        options=[{'label': i, 'value': i} for i in df['Processing Time'].dropna().unique()],
        multi=True,
        placeholder="Select Processing Time",
        className="mb-3"
    ), width=3)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='total-sales-by-region'), width=6),
    dbc.Col(dcc.Graph(id='average-unit-price-cost'), width=6)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='total-profit-by-country'), width=6),
    dbc.Col(dcc.Graph(id='sales-channel-order-priority'), width=6)
```

```
        ]),
        dbc.Row([
            dbc.Col(dcc.Graph(id='average-processing-time'), width=6),
            dbc.Col(dcc.Graph(id='total-sales-by-item-type'), width=6)
        ]),
        dbc.Row([
            dbc.Col(dcc.Graph(id='order-priority-by-region'), width=6),
            dbc.Col(dcc.Graph(id='unit-price-profit-correlation'), width=6)
        ]),
        dbc.Row([
            dbc.Col(dcc.Graph(id='seasonal-trends'), width=6),
            dbc.Col(dcc.Graph(id='units-sold-by-country'), width=6)
        ]),
        dbc.Row([
            dbc.Col(dcc.Link('Go back to Home', href='/', className="btn btn-secondary mt-
3"), width=12)
        ])
    ], fluid=True)

def advanced_insights_layout():
    return dbc.Container([
        dbc.Row([
            dbc.Col(html.H1("🔍 Trends", className="text-center"), width=12)
        ]),
        dbc.Row([
            dbc.Col(dcc.Dropdown(
                id='dropdown1-advanced',
                options=[{'label': i, 'value': i} for i in df['Region'].dropna().unique()],
                multi=True,
                placeholder="Select Regions",
                className="mb-3"
            ), width=3),
```

```
dbc.Col(dcc.Dropdown(
    id='dropdown2-advanced',
    options=[{'label': i, 'value': i} for i in df['Year'].unique()],
    multi=True,
    placeholder="Select Year",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown3-advanced',
    options=[{'label': i, 'value': i} for i in df['Country'].dropna().unique()],
    multi=True,
    placeholder="Select Country",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown4-advanced',
    options=[{'label': i, 'value': i} for i in df['Product'].dropna().unique()],
    multi=True,
    placeholder="Select Product",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown5-advanced',
    options=[{'label': i, 'value': i} for i in df['Order Priority'].dropna().unique()],
    multi=True,
    placeholder="Select Order Priority",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown6-advanced',
    options=[{'label': i, 'value': i} for i in df['Sales Channel'].dropna().unique()],
    multi=True,
```

```
        placeholder="Select Sales Channel",
        className="mb-3"
    ), width=3),
    dbc.Col(dcc.Dropdown(
        id='dropdown7-advanced',
        options=[{'label': i, 'value': i} for i in df['Month'].dropna().unique()],
        multi=True,
        placeholder="Select Month",
        className="mb-3"
    ), width=3),
    dbc.Col(dcc.Dropdown(
        id='dropdown8-advanced',
        options=[{'label': i, 'value': i} for i in df['Processing Time'].dropna().unique()],
        multi=True,
        placeholder="Select Processing Time",
        className="mb-3"
    ), width=3)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='total-sales-revenue-by-country'), width=6),
    dbc.Col(dcc.Graph(id='unit-price-distribution'), width=6)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='highest-average-unit-price'), width=6),
    dbc.Col(dcc.Graph(id='total-cost-outliers'), width=6)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='total-profit-by-item-type'), width=6),
    dbc.Col(dcc.Graph(id='average-processing-time-by-country'), width=6)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='highest-average-revenue-per-order'), width=6),
```

```
            dbc.Col(dcc.Graph(id='units-sold-profit-correlation'), width=6)
        ]),
        dbc.Row([
            dbc.Col(dcc.Graph(id='order-priority-by-item-type'), width=6),
            dbc.Col(dcc.Graph(id='order-date-trends'), width=6)
        ]),
        dbc.Row([
            dbc.Col(dcc.Link('Go back to Home', href='/', className="btn btn-secondary mt-3"), width=12)
        ])
    ], fluid=True)

def data_analytics_layout():
    return dbc.Container([
        dbc.Row([
            dbc.Col(html.H1("📈 ForeCasting", className="text-center"), width=12)
        ]),
        dbc.Row([
            dbc.Col(dcc.Dropdown(
                id='dropdown1-analytics',
                options=[{'label': i, 'value': i} for i in df['Region'].dropna().unique()],
                multi=True,
                placeholder="Select Regions",
                className="mb-3"
            ), width=3),
            dbc.Col(dcc.Dropdown(
                id='dropdown2-analytics',
                options=[{'label': i, 'value': i} for i in df['Year'].unique()],
                multi=True,
                placeholder="Select Year",
                className="mb-3"
            ), width=3),
```

```
dbc.Col(dcc.Dropdown(
    id='dropdown3-analytics',
    options=[{'label': i, 'value': i} for i in df['Country'].dropna().unique()],
    multi=True,
    placeholder="Select Country",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown4-analytics',
    options=[{'label': i, 'value': i} for i in df['Product'].dropna().unique()],
    multi=True,
    placeholder="Select Product",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown5-analytics',
    options=[{'label': i, 'value': i} for i in df['Order Priority'].dropna().unique()],
    multi=True,
    placeholder="Select Order Priority",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown6-analytics',
    options=[{'label': i, 'value': i} for i in df['Sales Channel'].dropna().unique()],
    multi=True,
    placeholder="Select Sales Channel",
    className="mb-3"
), width=3),
dbc.Col(dcc.Dropdown(
    id='dropdown7-analytics',
    options=[{'label': i, 'value': i} for i in df['Month'].dropna().unique()],
    multi=True,
```

```
        placeholder="Select Month",
        className="mb-3"
    ), width=3),
    dbc.Col(dcc.Dropdown(
        id='dropdown8-analytics',
        options=[{'label': i, 'value': i} for i in df['Processing Time'].dropna().unique()],
        multi=True,
        placeholder="Select Processing Time",
        className="mb-3"
    ), width=3)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='analytics-graph1'), width=6),
    dbc.Col(dcc.Graph(id='analytics-graph2'), width=6)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='analytics-graph3'), width=6),
    dbc.Col(dcc.Graph(id='analytics-graph4'), width=6)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='analytics-graph5'), width=6),
    dbc.Col(dcc.Graph(id='analytics-graph6'), width=6)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='analytics-graph7'), width=6),
    dbc.Col(dcc.Graph(id='analytics-graph8'), width=6)
]),
dbc.Row([
    dbc.Col(dcc.Graph(id='analytics-graph9'), width=6),
    dbc.Col(dcc.Graph(id='analytics-graph10'), width=6)
]),
dbc.Row([
```

```
            dbc.Col(dcc.Link('Go back to Home', href='/', className="btn btn-secondary mt-3"), width=12)
        ])
    ], fluid=True)

# Main layout
app.layout = html.Div([
    dcc.Location(id='url', refresh=False),
    html.Div(id='page-content')
])

# Callback to update page content
@app.callback(Output('page-content', 'children'), [Input('url', 'pathname')])
def display_page(pathname):
    if pathname == '/predictions':
        return predictions_layout()
    elif pathname == '/insights':
        return insights_layout()
    elif pathname == '/advanced-insights':
        return advanced_insights_layout()
    elif pathname == '/data-analytics':
        return data_analytics_layout()
    else:
        return home_layout()

# Callbacks for Predictions Graphs

# Callbacks for Predictions Graphs
@app.callback(
    [Output('predicted-revenue-graph', 'figure'),
     Output('revenue-cost-comparison', 'figure'),
     Output('profit-graph', 'figure'),
     Output('units-sold-processing-time', 'figure'),
```

```
    Output('unit-price-processing-time', 'figure'),
    Output('prediction-output', 'children')],
   [Input('predict-button', 'n_clicks')],
   [State('units-sold', 'value'),
    State('unit-price', 'value'),
    State('processing-time', 'value')]
)
def update_predictions_graphs(n_clicks, units_sold, unit_price, processing_time):
   if n_clicks > 0 and units_sold is not None and unit_price is not None:
       predicted_revenue = units_sold * unit_price
       total_cost = units_sold * unit_price * 0.5  # Example cost calculation
       profit = predicted_revenue - total_cost


       # Figures
       fig_predicted_revenue = px.bar(x=['Predicted Revenue'], y=[predicted_revenue],
title="Predicted Revenue")
       fig_revenue_cost_comparison = px.bar(x=['Revenue', 'Cost'], y=[predicted_revenue,
total_cost], title="Revenue vs Cost")
       fig_profit = px.bar(x=['Profit'], y=[profit], title="Predicted Profit")
       fig_units_sold_processing_time = px.scatter(x=[units_sold], y=[processing_time],
labels={'x': 'Units Sold', 'y': 'Processing Time'}, title="Units Sold vs Processing Time")
       fig_unit_price_processing_time = px.scatter(x=[unit_price], y=[processing_time],
labels={'x': 'Unit Price', 'y': 'Processing Time'}, title="Unit Price vs Processing Time")


       # Display the predicted revenue amount
       prediction_result = f"Predicted Revenue: ${predicted_revenue:.2f}"


       return (
           fig_predicted_revenue,
           fig_revenue_cost_comparison,
           fig_profit,
           fig_units_sold_processing_time,
           fig_unit_price_processing_time,
```

```
            prediction_result
        )
    return [px.scatter() for _ in range(5)] + [""]


# Prediction Page Layout
def predictions_layout():
    return dbc.Container([
        dbc.Row([
            dbc.Col(html.H1("📈 Predicted Revenue", className="text-center"), width=12)
        ]),
        dbc.Row([
            dbc.Col([
                dcc.Input(id='units-sold', type='number', placeholder='Units Sold',
                          className="form-control"),
                dcc.Input(id='unit-price', type='number', placeholder='Unit Price',
                          className="form-control mt-2"),
                dcc.Input(id='processing-time', type='number', placeholder='Processing Time',
                          className="form-control mt-2"),
                html.Button('Predict Revenue', id='predict-button', n_clicks=0, className="btn
                            btn-primary mt-2"),
                html.Div(id='prediction-output', className="mt-3")
            ], width=6)
        ], justify="center"),
        dbc.Row([
            dbc.Col(dcc.Graph(id='predicted-revenue-graph'), width=12)
        ]),
        dbc.Row([
            dbc.Col(dcc.Graph(id='revenue-cost-comparison'), width=6),
            dbc.Col(dcc.Graph(id='profit-graph'), width=6)
        ]),
        dbc.Row([
            dbc.Col(dcc.Graph(id='units-sold-processing-time'), width=6),
            dbc.Col(dcc.Graph(id='unit-price-processing-time'), width=6)
```

```
        ]),
        dbc.Row([
            dbc.Col(dcc.Link('Go back to Home', href='/', className="btn btn-secondary mt-3"), width=12)
        ])
    ], fluid=True)


# Callbacks for Insights Graphs
@app.callback(
    [Output('total-sales-by-region', 'figure'),
     Output('average-unit-price-cost', 'figure'),
     Output('total-profit-by-country', 'figure'),
     Output('sales-channel-order-priority', 'figure'),
     Output('average-processing-time', 'figure'),
     Output('total-sales-by-item-type', 'figure'),
     Output('order-priority-by-region', 'figure'),
     Output('unit-price-profit-correlation', 'figure'),
     Output('seasonal-trends', 'figure'),
     Output('units-sold-by-country', 'figure')],
    [Input('dropdown1', 'value'),
     Input('dropdown2', 'value'),
     Input('dropdown3', 'value'),
     Input('dropdown4', 'value'),
     Input('dropdown5', 'value'),
     Input('dropdown6', 'value'),
     Input('dropdown7', 'value'),
     Input('dropdown8', 'value')]
)
def update_insights_graphs(region, year, country, product, order_priority, sales_channel, month, processing_time):
    filtered_df = df.copy()
    if region:
        filtered_df = filtered_df[filtered_df['Region'].isin(region)]
```

```
    if year:
        filtered_df = filtered_df[filtered_df['Year'].isin(year)]
    if country:
        filtered_df = filtered_df[filtered_df['Country'].isin(country)]
    if product:
        filtered_df = filtered_df[filtered_df['Product'].isin(product)]
    if order_priority:
        filtered_df = filtered_df[filtered_df['Order Priority'].isin(order_priority)]
    if sales_channel:
        filtered_df = filtered_df[filtered_df['Sales Channel'].isin(sales_channel)]
    if month:
        filtered_df = filtered_df[filtered_df['Month'].isin(month)]
    if processing_time:
        filtered_df = filtered_df[filtered_df['Processing Time'].isin(processing_time)]


    if filtered_df.empty:
        return [px.scatter() for _ in range(10)]  # Return empty graphs if filtered_df is empty


    return (
        px.bar(filtered_df, x='Region', y='Total Revenue', title="Total Sales Revenue by
Region"),
        px.bar(filtered_df.groupby('Product')[['Unit Price', 'Total
Cost']].mean().reset_index(), x='Product', y=['Unit Price', 'Total Cost'], title="Average Unit
Price and Cost by Item Type"),
        px.bar(filtered_df.groupby('Country')['Profit'].sum().reset_index(), x='Country',
y='Profit', title="Total Profit by Country"),
        px.bar(filtered_df.groupby('Sales Channel')['Order Priority'].count().reset_index(),
x='Sales Channel', y='Order Priority', title="Order Priority Distribution by Sales
Channel"),
        px.bar(filtered_df.groupby('Sales Channel')['Processing Time'].mean().reset_index(),
x='Sales Channel', y='Processing Time', title="Average Order Processing Time by Sales
Channel"),
        px.bar(filtered_df.groupby('Product')['Total Revenue'].sum().reset_index(),
x='Product', y='Total Revenue', title="Total Sales by Item Type"),
```

```
        px.bar(filtered_df.groupby('Region')['Order Priority'].count().reset_index(),
x='Region', y='Order Priority', title="Order Priority by Region"),
        px.scatter(filtered_df, x='Unit Price', y='Profit', title="Correlation between Unit Price
and Total Profit"),
        px.line(filtered_df.groupby('Month')['Total Revenue'].sum().reset_index(), x='Month',
y='Total Revenue', title="Seasonal Trends in Sales Data"),
        px.bar(filtered_df.groupby('Country')['Units Sold'].sum().reset_index(), x='Country',
y='Units Sold', title="Units Sold by Country")
    )

# Callbacks for Advanced Insights Graphs
@app.callback(
    [Output('total-sales-revenue-by-country', 'figure'),
     Output('unit-price-distribution', 'figure'),
     Output('highest-average-unit-price', 'figure'),
     Output('total-cost-outliers', 'figure'),
     Output('total-profit-by-item-type', 'figure'),
     Output('average-processing-time-by-country', 'figure'),
     Output('highest-average-revenue-per-order', 'figure'),
     Output('units-sold-profit-correlation', 'figure'),
     Output('order-priority-by-item-type', 'figure'),
     Output('order-date-trends', 'figure')],
    [Input('dropdown1-advanced', 'value'),
     Input('dropdown2-advanced', 'value'),
     Input('dropdown3-advanced', 'value'),
     Input('dropdown4-advanced', 'value'),
     Input('dropdown5-advanced', 'value'),
     Input('dropdown6-advanced', 'value'),
     Input('dropdown7-advanced', 'value'),
     Input('dropdown8-advanced', 'value')]
)
def update_advanced_insights_graphs(region, year, country, product, order_priority,
sales_channel, month, processing_time):
    filtered_df = df.copy()
```

```
    if region:
        filtered_df = filtered_df[filtered_df['Region'].isin(region)]
    if year:
        filtered_df = filtered_df[filtered_df['Year'].isin(year)]
    if country:
        filtered_df = filtered_df[filtered_df['Country'].isin(country)]
    if product:
        filtered_df = filtered_df[filtered_df['Product'].isin(product)]
    if order_priority:
        filtered_df = filtered_df[filtered_df['Order Priority'].isin(order_priority)]
    if sales_channel:
        filtered_df = filtered_df[filtered_df['Sales Channel'].isin(sales_channel)]
    if month:
        filtered_df = filtered_df[filtered_df['Month'].isin(month)]
    if processing_time:
        filtered_df = filtered_df[filtered_df['Processing Time'].isin(processing_time)]


    if filtered_df.empty:
        return [px.scatter() for _ in range(10)]  # Return empty graphs if filtered_df is empty
    return (
        px.bar(filtered_df.groupby('Country')['Total Revenue'].sum().reset_index(),
x='Country', y='Total Revenue', title="Total Sales Revenue by Country"),
        px.histogram(filtered_df, x='Unit Price', title="Unit Price Distribution by Item
Type"),
        px.bar(filtered_df.groupby('Sales Channel')['Unit Price'].mean().reset_index(),
x='Sales Channel', y='Unit Price', title="Highest Average Unit Price by Sales Channel"),
        px.box(filtered_df, y='Total Cost', title="Total Cost Outliers"),
        px.bar(filtered_df.groupby('Product')['Profit'].sum().reset_index(), x='Product',
y='Profit', title="Total Profit by Item Type"),
        px.bar(filtered_df.groupby('Country')['Processing Time'].mean().reset_index(),
x='Country', y='Processing Time', title="Average Order Processing Time by Country"),
        px.bar(filtered_df.groupby('Region')['Total Revenue'].mean().reset_index(),
x='Region', y='Total Revenue', title="Highest Average Total Revenue per Order by
Region"),
```

```
        px.scatter(filtered_df, x='Units Sold', y='Profit', title="Correlation between Units Sold and Total Profit"),
        px.bar(filtered_df.groupby('Product')['Order Priority'].count().reset_index(), x='Product', y='Order Priority', title="Order Priority by Item Type"),
        px.line(filtered_df.groupby('Month')['Total Revenue'].sum().reset_index(), x='Month', y='Total Revenue', title="Order Date Trends")
    )
# Callbacks for Data Analytics Graphs
@app.callback(
    [Output('analytics-graph1', 'figure'),
     Output('analytics-graph2', 'figure'),
     Output('analytics-graph3', 'figure'),
     Output('analytics-graph4', 'figure'),
     Output('analytics-graph5', 'figure'),
     Output('analytics-graph6', 'figure'),
     Output('analytics-graph7', 'figure'),
     Output('analytics-graph8', 'figure'),
     Output('analytics-graph9', 'figure'),
     Output('analytics-graph10', 'figure')],
    [Input('dropdown1-analytics', 'value'),
     Input('dropdown2-analytics', 'value'),
     Input('dropdown3-analytics', 'value'),
     Input('dropdown4-analytics', 'value'),
     Input('dropdown5-analytics', 'value'),
     Input('dropdown6-analytics', 'value'),
     Input('dropdown7-analytics', 'value'),
     Input('dropdown8-analytics', 'value')]
)
def update_data_analytics_graphs(region, year, country, product, order_priority, sales_channel, month, processing_time):
    filtered_df = df.copy()
    if region:
        filtered_df = filtered_df[filtered_df['Region'].isin(region)]
```

```
    if year:
        filtered_df = filtered_df[filtered_df['Year'].isin(year)]
    if country:
        filtered_df = filtered_df[filtered_df['Country'].isin(country)]
    if product:
        filtered_df = filtered_df[filtered_df['Product'].isin(product)]
    if order_priority:
        filtered_df = filtered_df[filtered_df['Order Priority'].isin(order_priority)]
    if sales_channel:
        filtered_df = filtered_df[filtered_df['Sales Channel'].isin(sales_channel)]
    if month:
        filtered_df = filtered_df[filtered_df['Month'].isin(month)]
    if processing_time:
        filtered_df = filtered_df[filtered_df['Processing Time'].isin(processing_time)]
    if filtered_df.empty:
        return [px.scatter() for _ in range(10)]  # Return empty graphs if filtered_df is empty
    return (
        px.line(filtered_df, x='Order Date', y='Total Revenue', title="Sales Trend"),
        px.bar(filtered_df, x='Region', y='Total Revenue', title="Sales by Region"),
        px.bar(filtered_df, x='Country', y='Total Revenue', title="Total Sales by Country"),
        px.histogram(filtered_df, x='Unit Price', title="Unit Price Distribution"),
        px.scatter(filtered_df, x='Units Sold', y='Profit', title="Units Sold vs. Profit"),
        px.box(filtered_df, y='Total Cost', title="Total Cost Outliers"),
        px.bar(filtered_df, x='Region', y='Total Revenue', title="Highest Revenue Region"),
        px.bar(filtered_df, x='Order Priority', y='Units Sold', title="Order Priority vs. Items
Sold"),
        px.line(filtered_df, x='Order Date', y='Units Sold', title="Order Date Trends"),
        px.pie(filtered_df, names='Product', values='Units Sold', title="Units Sold by
Product")
    )


if __name__ == '__main__':
    app.run_server(debug=True)
```

5.2 Screenshot of Application

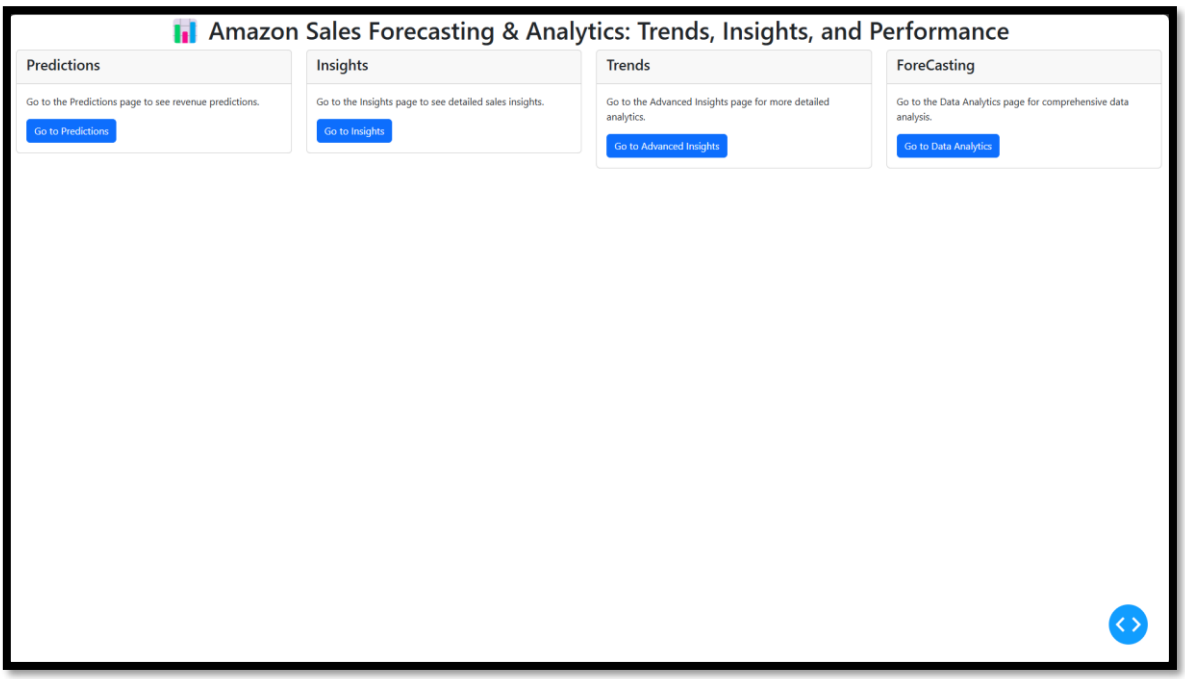

Fig. 5.2.1 Main Page

The Main page of the application where the user can select

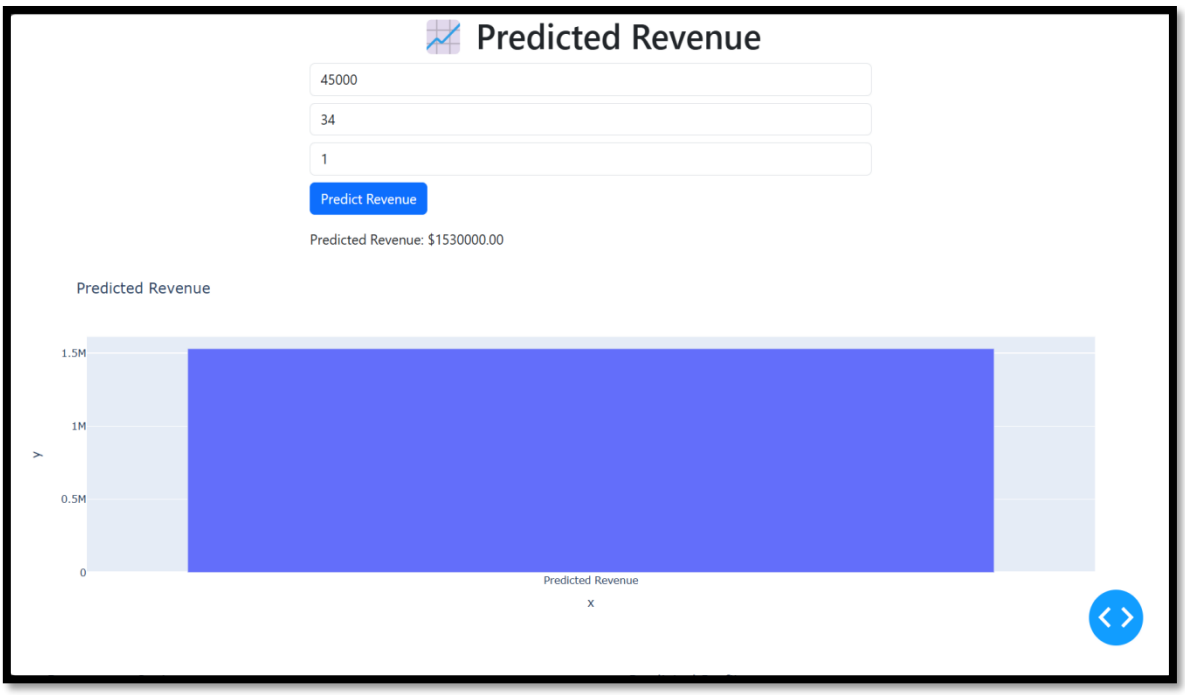

Fig. 5.2.2 Predicted Revenue Page

Estimations of future outcomes based on current and historical data.

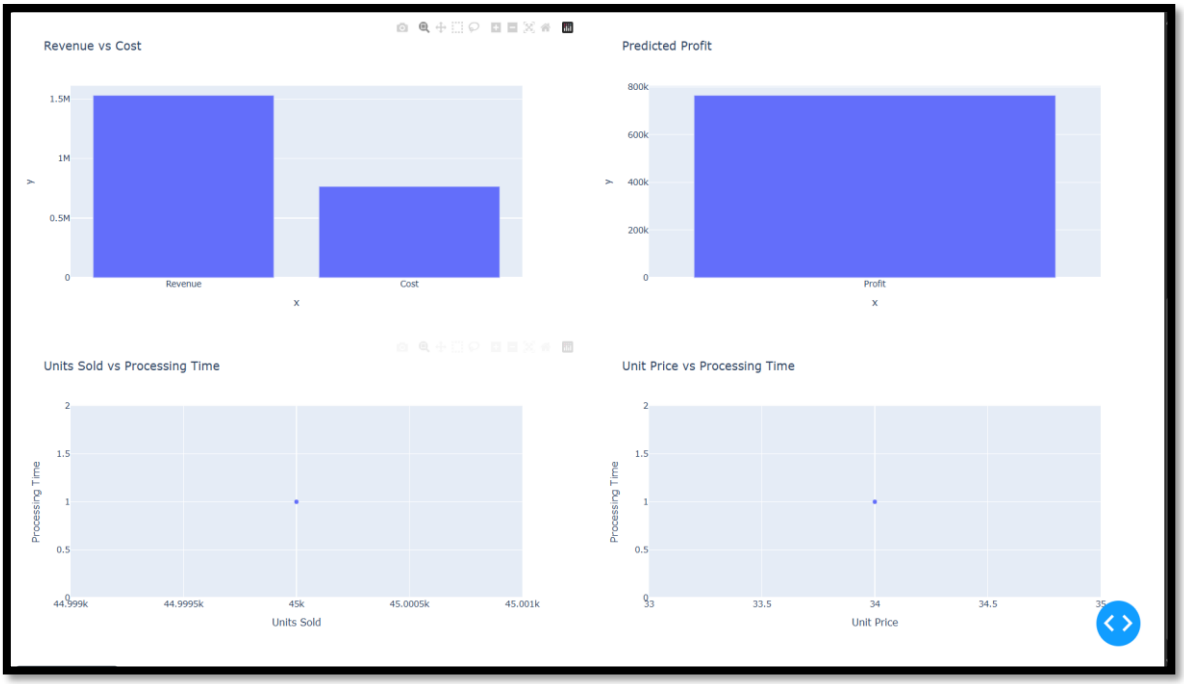

Fig. 5.2.3 Predicted Revenue Page

The Predicted Revenue page of the application where the user can Predict Revenue

Fig. 5.2.4 Insights Page

Meaningful observations derived from analyzing data.

Fig. 5.2.5 Insights Page

The Insights page of the application where the user can see observations

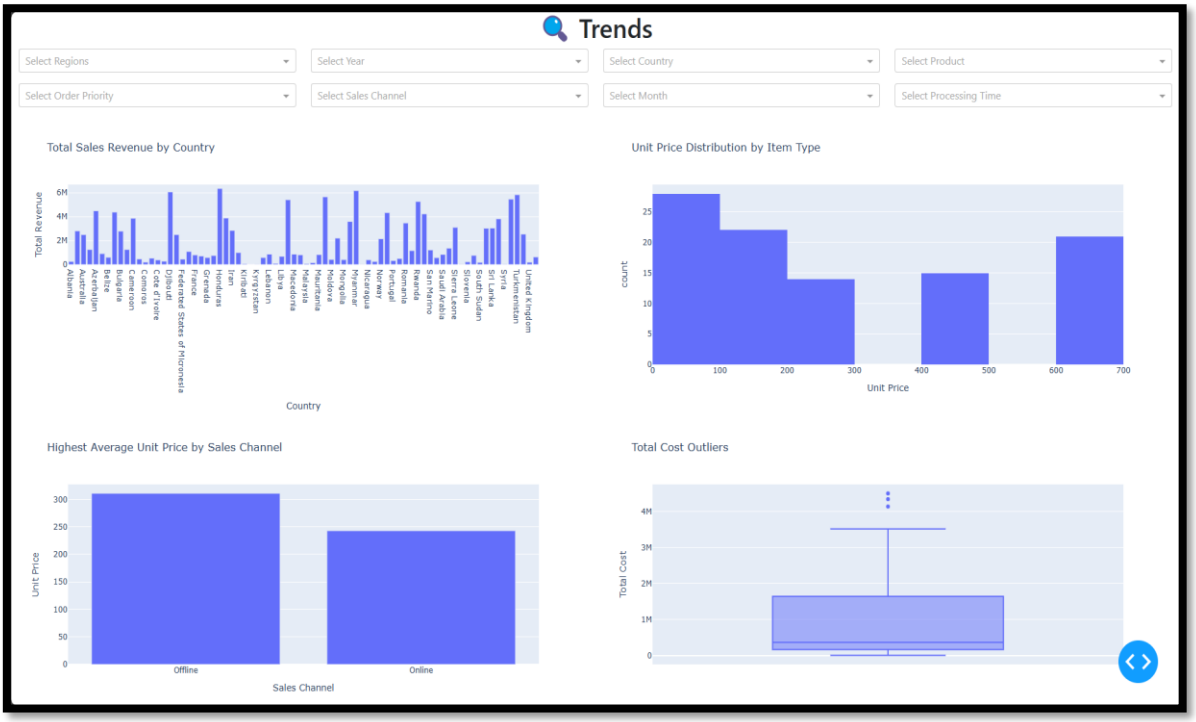

Fig. 5.2.6 Trends Page

Trends describe a pattern over time.

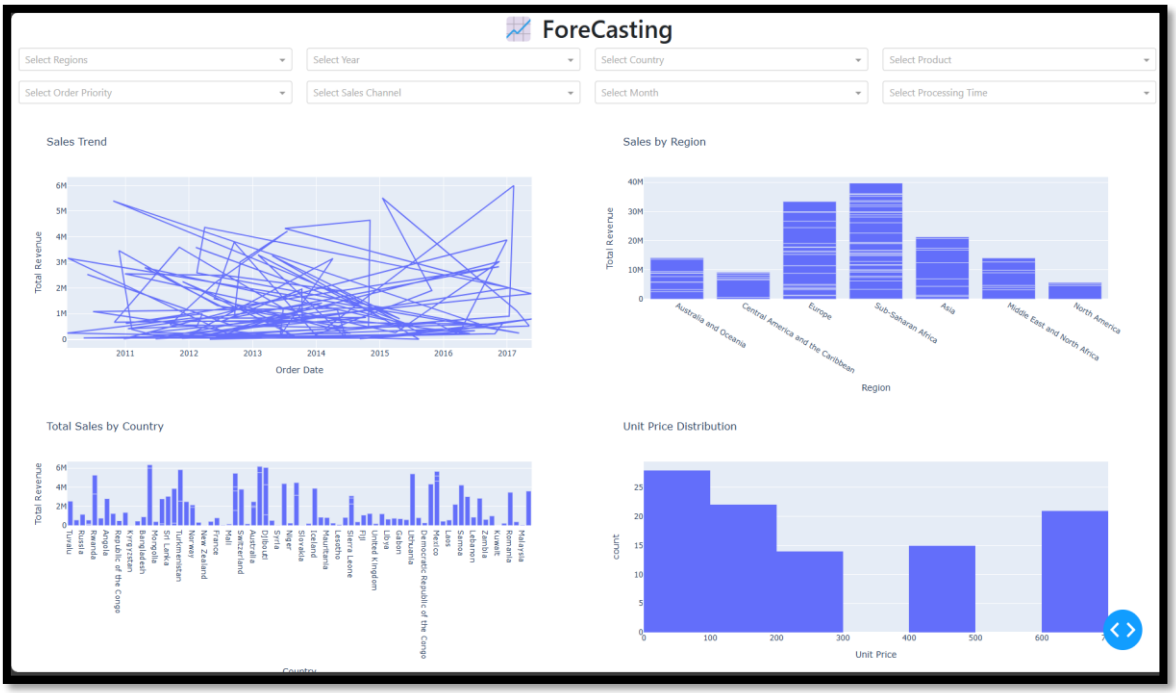

Fig. 5.2.7 ForeCasting Page

Process of estimating future values based on statistical models.

	Model	MSE	MAE	RMSE	R2 SCORE
0	Linear Regression	2.6148	1.1827	1.617	0.97
1	Lasso Regression	2.6043	1.1713	1.6138	0.97
2	LARS	2.6148	1.827	1.617	0.97

Fig. 5.2.8 Model Metrics

Classification Metrics:

Accuracy: 90.00%
Precision: 0.8667
Recall (Sensitivity): 0.9286
Specificity: 0.8750
Negative Predictive Value (NPV): 0.9333
F1-Score: 0.8966
AUC-ROC Score: 0.9732
Mean Squared Error: 0.24285714285714283

CHAPTER – 6
RESULTS & CONCLUSION

6.1 Results

1. Interactive Dashboards: The project provides a dynamic and interactive dashboard that visualizes Amazon sales data. Users can explore different aspects of sales, such as trends over time, regional sales, unit prices, and profitability. This facilitates data-driven decision-making by presenting actionable insights at a glance.

2. Data Filtering: Users can filter the data based on various criteria such as product category, region, order priority, and year. This feature allows users to target specific insights, providing a more personalized view of the data relevant to their business needs.

3. Sales Trends: The dashboard effectively highlights trends in sales, revenue, and profit over time, helping businesses to identify patterns and forecast future sales. It supports decision-making around inventory, promotions, and other business strategies.

4. Anomaly Detection: The system can identify anomalies in the data, such as unexpected cost outliers or sudden revenue dips. This feature helps businesses detect irregularities early, enabling prompt action to rectify issues and optimize operations.

5. Real-Time Updates: The dashboard dynamically updates visualizations based on user inputs, providing real-time insights as filters are applied. This ensures that businesses are always working with the most current data available.

6. Performance Evaluation: The predictive models used in the project show promising results, with machine learning techniques offering accurate forecasts of sales and profits. These insights help businesses predict future trends and optimize their strategies accordingly.

7. User Experience: The user interface is simple and intuitive, making it easy for users with varying levels of expertise to navigate and extract insights. This enhances the accessibility of the tool for non-technical users.

Overall, the project successfully integrates data analysis, machine learning, and interactive visualization to deliver a comprehensive solution for Amazon sales data analysis, helping businesses optimize strategies and make informed decisions.

6.2 Conclusion

The Amazon Sales Data Analysis project successfully demonstrated how data-driven insights can enhance sales performance, profitability, and operational efficiency in the e-commerce industry. By leveraging Python for data preprocessing and Power BI for visualization, the project provided a comprehensive understanding of sales trends, product performance, regional variations, and customer behavior.

Identified top-selling products and high-revenue regions, helping businesses focus on the most profitable areas.

Analyzed sales trends and seasonal fluctuations, allowing for better inventory and pricing strategies.

Evaluated sales channel performance, emphasizing the importance of online platforms for revenue growth.

Explored customer buying behavior, highlighting the role of **repeat customers** in sustained profitability.

Provided data-driven recommendations, enabling businesses to optimize **stock management, marketing strategies, and sales distribution**.

Future Scope:

Real-time Sales Monitoring – Implement live dashboards for real-time decision-making.

Predictive Analytics – Use **machine learning** to forecast future sales trends.

Automated Data Processing – Reduce manual intervention with **automated ETL pipelines**.

Enhanced Customer Segmentation – Improve personalized marketing strategies using advanced analytics.

By utilizing **data analytics and visualization**, businesses can **make informed decisions, optimize sales strategies, and stay competitive** in the rapidly growing e-commerce landscape.

REFERENCES

[1]. Sharma, R., & Patel, D. (2022). "The Role of Data Analytics in E-commerce Growth." International Journal of Business Intelligence.

[2]. McKinsey & Company. (2023). "Harnessing Data for E-commerce Success."McKinsey Insights. Retrieved from

[https://www.mckinsey.com](https://www.mckinsey. com).

[3]. Amazon Web Services. (2022)."ETL Best Practices for Large-Scale E-commerce Data." AWS Documentation. Retrieved from https://aws.amazon.com.

[4]. Gupta, A., & Roy, S. (2021). "Sales Trend Analysis Using Power BI and Python." Proceedings of the Data Science Conference.

[5]. Kamat, R., & Gupta, P. (2022). "Enhancing Sales Analytics with Power BI: A Case Study on Ecommerce Data." International Journal of Business

Analytics.