AI-Powered Sales Forecasting and Dashboard Analytics for E-Commerce

A Project Report submitted to
Jawaharlal Nehru Technological University
in partial fulfillment of the requirements for the award of Degree of

BACHELOR OF TECHNOLOGY
in
COMPUTER SCIENCE & ENGINEERING – CYBER SECURITY

Submitted by

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Under the Guidance of

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June, 2025

CERTIFICATE

This is to certify that the Mini-project/project entitled AI-Powered Sales Forecasting and Dashboard Analytics for E-Commerce is being submitted by Ms. MADHUGNA.K bearing Roll No. 22WJ1A6224, in partial fulfilment for the award of the Degree of Bachelor of the Technology in Cyber Security to the Jawaharlal Nehru Technological University is a record of Bonafide work carried out by him/her/them under my guidance and supervision.

The results embodied in this Mini-project/project report have not been submitted to any other University or Institute for the award of any Degree or Diploma

Internal Guide	Mini Project Co-Ordinator	Head of the Department
Dr. Ch. Subha Lakshmi, Ph.D	**Mr. Ch. Upendher, M.tech(Ph.D)**	**Dr. Ch. Subha Lakshmi, Ph.D**
HOD-CSE-CYBER SECURITY	**Asst professor**	**HOD-CSE-CYBER SECURITY**

Declaration of Student

I, MADHUGNA.K (22WJ1A6224), hereby declare that the mini project titled "AI-POWERED SALES FORECASTING AND DASHBOARD ANALYTICS FOR E-COMMERCE" has been carried out by us as part of the requirements for the award of the Degree of Bachelor of Technology in the Department of CSE-Cyber Security at Guru Nanak Institutions Technical Campus.

I confirm the following:

1. The project was undertaken by us under the supervision of our guide, Dr. Ch. Subba Lakshmi, from the selection of the topic to the completion of the final report.
2. We have ensured that the results presented in the report are accurate and based on our original work.
3. To the best of our knowledge, the content of this report is free from plagiarism and adheres to ethical standards.
4. Each member of the team has contributed significantly and appropriately to the project work.
5. The project report has been prepared with diligence, ensuring clarity, accuracy, and adherence to academic standards.

I further declare that this report has not been submitted, in part or full, to any other institution or university for the award of any degree or diploma.

MADHUGNA.K

22WJ1A6224 Signature

Date:

Place:

Declaration of Guide

I, Dr. Ch. Subha Lakshmi, Ph.D, hereby declare that I have guided the mini project titled "AI-POWERED SALES FORECASTING AND DASHBOARD ANALYTICS FOR E-COMMERCE" undertaken by MADHUGNA.K (22WJ1A6224). This project was carried out towards the fulfillment of the requirements for the award of the Degree of Bachelor of Technology in CSE-Cyber Security at Guru Nanak Institutions Technical Campus.

As the guide, I confirm the following:

1. I have overseen the entire project process, from the selection of the project title to the submission of the final report.
2. I have reviewed and certified the accuracy and relevance of the results presented in the report.
3. The contributions of each student have been appropriately recognized and assessed.
4. The project report has been prepared under my supervision, ensuring adherence to high standards of quality, clarity, and structure.

I further certify that this project report has not been previously submitted in part or full for the award of any degree or diploma by any institution or university.

Name of Guide: Dr. Ch. Subha Lakshmi, Ph.D

Date:

Place: Signature of the Guide

Name of HOD: Dr. Ch. Subha Lakshmi, Ph.D

Department: CSE-CYBER SECURITY Signature of the HOD

Date:

Place:

ACKNOWLEDGEMENT

I would like to express our sincere gratitude to our internal guide, **Dr. Ch. Subha Lakshmi, Ph.D, [**HOD-CSE_CYBER SECURITY], [CSE_CYBER SECURITY], for her valuable guidance, encouragement, and continuous support throughout the duration of this project.

I am also thankful to **Dr. Ch. Subha Lakshmi, Ph.D,** [HOD-CSE-CYBER SECURITY], [CSE-CYBER SECURITY], for her expert supervision and helpful suggestions, which contributed significantly to the successful completion of this project.

I would also like to thank the faculty members of the **CSE-CYBER SECURITY** and the Lab Technicians for their assistance and cooperation during the practical work of our project.

I am grateful to our friends and well-wishers for their encouragement, collaboration, and useful feedback throughout the project journey.

Lastly, I sincerely thank our parents for their constant support, patience, and motivation, which helped us complete this project successfully.

MADHUGNA.K 22WJ1A6224

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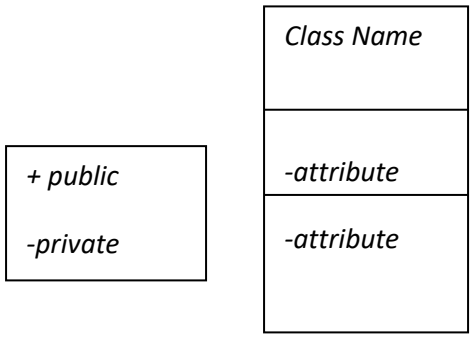
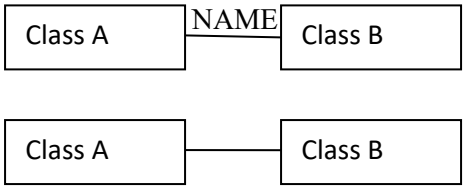
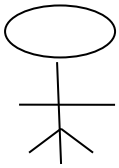
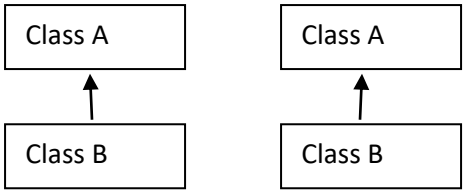
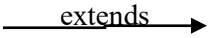
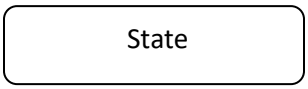
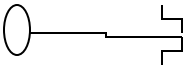
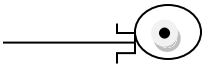
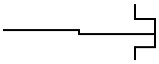
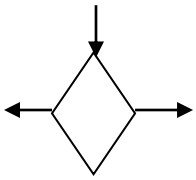
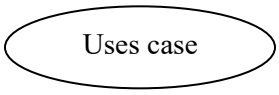
ABSTRACT:

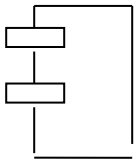
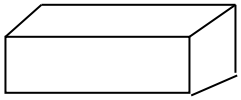
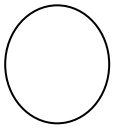
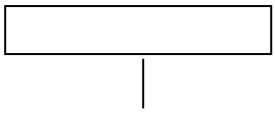
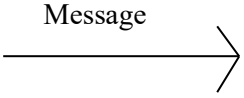
The AI-Powered Sales Forecasting and Dashboard Analytics for E-Commerce system utilizes Random Forest Regression to predict sales trends, optimize inventory management, and improve business decision-making. By analysing historical sales data, customer purchasing patterns, and external market trends, the system generates accurate forecasts, enabling businesses to plan efficiently and reduce financial risks. The integration of AI-driven predictive analytics enhances decision-making by identifying seasonal demand fluctuations, sales patterns, and revenue projections. The proposed system employs Random Forest Regression, a robust ensemble learning technique, to improve forecasting accuracy by handling large datasets and reducing over fitting. Power BI is used for data visualization, offering dynamic dashboards with interactive charts, real-time KPIs, and trend analysis. The system processes data using Python, Pandas, and NumPy, ensuring efficient data handling before feeding it into the predictive model. By automating sales forecasting and providing real-time analytical insights, this system helps e-commerce businesses make data-driven decisions, improve resource allocation, and enhance profitability. Future enhancements may include real-time demand forecasting, integration with external market trends, and AI-driven recommendation systems to further optimize business performance.

LIST OF FIGURES

LIST OF SYMBOLS

S.NO	NOTATION NAME	NOTATION	DESCRIPTION
1.	Class		Represents a collection of similar entities grouped together.
2.	Association		Associations represents static relationships between classes. Roles represents the way the two classes see each other.
3.	Actor		It aggregates several classes into a single classes.
4.	Aggregation		Interaction between the system and external environment

5.	Relation (extends)		Extends relationship is used when one use case is similar to another use case but does a bit more.
6.	Communication		Communication between various use cases.
7.	State		State of the processes.
8.	Initial State		Initial state of the object
9.	Final state		Final state of the object
10.	Control flow		Represents various control flow between the states.
11.	Decision box		Represents decision making process from a constraint
12.	Use case		Interact ion between the system and external environment.

13.	Component		Represents physical modules which are a collection of components.
14.	Node		Represents physical modules which are a collection of components.
15.	Data Process/State		A circle in DFD represents a state or process which has been triggered due to some event or action.
16.	External entity		Represents external entities such as keyboard, sensors, etc.
17.	Transition		Represents communication that occurs between processes.
18.	Object Lifeline		Represents the vertical dimensions that the object communications.
19.	Message	Message 	Represents the message exchanged.

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CHAPTER-1

INTRODUCTION

1.1 INTRODUCTION:

In today's competitive e-commerce landscape, accurate sales forecasting plays a critical role in driving efficient business operations and maximizing profitability. The "AI-Powered Sales Forecasting and Dashboard Analytics for E-Commerce" system leverages advanced machine learning techniques to provide data-driven insights into sales trends. By analyzing historical sales data, customer purchasing behavior, and external market factors, the system delivers precise forecasts to help businesses make informed decisions. This intelligent system integrates Random Forest Regression, a powerful ensemble learning algorithm, with interactive data visualization tools like Power BI to offer real-time insights and predictive analytics tailored to the dynamic needs of e-commerce platforms.

1.2 SCOPE OF THE PROJECT

The primary objective of this project is to build a robust sales forecasting system that improves decision-making through predictive analytics. Specific goals include enhancing forecasting accuracy using Random Forest Regression, automating the analysis of historical and market data, and providing visually rich dashboards for stakeholders. The system also aims to optimize inventory planning, reduce financial risks, and boost overall business performance. Future objectives involve incorporating real-time forecasting capabilities, integrating external market data, and developing AI-driven recommendation systems to further support strategic planning and customer engagement.

1.3 OBJECTIVE

The primary objective of this project is to build a robust sales forecasting system that improves decision-making through predictive analytics. Specific goals include enhancing forecasting accuracy using Random Forest Regression, automating the analysis of historical and market data, and providing visually rich dashboards for stakeholders. The system also aims to optimize inventory planning, reduce financial risks, and boost overall business performance. Future objectives involve incorporating real-time forecasting capabilities, integrating external market data, and developing AI-driven recommendation systems to further support strategic planning and customer engagement

1.4 EXISTING SYSTEM:

- The existing system utilizes Decision Tree Regression, a supervised learning algorithm that models data by recursively splitting it into smaller subsets based on feature values. It builds a tree-like structure where each internal node represents a decision based on a feature, and the leaf nodes provide the final prediction. The model works well for structured data and provides interpretable results.
- However, Decision Tree Regression tends to overfit when dealing with large datasets, leading to poor generalization on unseen data. Additionally, it is sensitive to small variations in data, making predictions unstable. The model also lacks robustness when handling high-dimensional or noisy datasets, affecting forecasting accuracy in dynamic environments like e-commerce sales prediction.

1.4.1 EXISTINGSYSTEM DISADVANTAGES:

- High Variance
- Limited Performance on Complex Data
- Lack of Smooth Predictions
- Scalability Issues

1.5 LITERATURE SURVEY

Title: AI-Powered Sales Forecasting: Transforming Accuracy and Efficiency in Predictive Analytics

Author: Premkumar Ganesan

Year: 2024.

Description: This study explores the integration of AI techniques, particularly Random Forest Regression, to enhance sales forecasting accuracy in e-commerce. By analyzing historical sales data and customer behavior, the research demonstrates how AI models can reduce forecasting errors and improve inventory management. The paper emphasizes the role of ensemble learning methods in handling large datasets and mitigating overfitting, leading to more reliable sales predictions.

Title: Forecasting E-Commerce Trends: Utilizing Linear Regression, Polynomial Regression, Random Forest, and Gradient Boosting for Accurate Sales and Demand Prediction

Author: Naresh Kumar Reddy Panga

Year: 2023.

Description: This research compares various machine learning models, including Random Forest and Gradient Boosting, for forecasting sales trends in e-commerce. The study highlights the superior performance of ensemble methods in capturing complex patterns in sales data, leading to improved demand prediction and strategic planning. The findings suggest that integrating these models can significantly enhance the accuracy of sales forecasts in the e-commerce sector.

Title: Leveraging Artificial Intelligence for Enhanced Sales Forecasting Accuracy: A Review of AI-Driven Techniques and Practical Applications in Customer Relationship Management Systems

Author: Z. Embong

Year: 2024.

Description: This paper reviews the application of AI-driven techniques, including Random Forest Regression, in sales forecasting within Customer Relationship Management (CRM) systems. It discusses how these models can process vast amounts of customer data to identify purchasing patterns and predict future sales, thereby aiding businesses in making informed decisions and optimizing their sales strategies.

Title: Enhancing Retail Sales Forecasting with Optimized Machine Learning Models

Author: Priyam Ganguly and Isha Mukherjee

Year: 2024

Description: This research focuses on optimizing machine learning models, particularly Random Forest, for retail sales forecasting. By employing hyperparameter tuning and cross-validation techniques, the study achieves significant improvements in prediction accuracy. The optimized Random Forest model outperforms traditional methods, demonstrating its effectiveness in handling complex sales data and providing reliable forecasts for inventory and resource management.

Title: Sales Forecasting Study Based on a Composite Model of Deep Learning and Random Forest

Author: Ziyao Wang and Yining Liu

Year: 2024**.**

Description: This study introduces a composite model integrating deep learning techniques with Random Forest (RF) to enhance sales forecasting accuracy in dynamic market environments. The model employs Convolutional Neural Networks (CNN) to extract complex features from time-series data and Bidirectional Long Short-Term Memory (BiLSTM) networks to capture dependencies in the data. Random Forest is utilized to reduce overfitting and achieve feature fusion through joint training, thereby optimizing prediction accuracy. Experimental results demonstrate that this composite model outperforms traditional models across various evaluation metrics, particularly in highly volatile markets, showcasing exceptional adaptability and stability.

1.6 PROPOSED SYSTEM

- The proposed system enhances sales forecasting accuracy by leveraging Random Forest Regression, an ensemble learning technique that combines multiple decision trees. Unlike the existing Decision Tree Regression, which is prone to overfitting, Random Forest improves prediction stability by averaging multiple tree outputs, reducing variance and enhancing generalization.
- This model efficiently handles large datasets, high-dimensional features, and missing data, making it well-suited for dynamic e-commerce environments. By using feature importance analysis, it identifies key factors influencing sales trends, enabling businesses to make more informed decisions. Additionally, Power BI is integrated for interactive and real-time data visualization, offering a comprehensive analytical dashboard for monitoring sales performance and market trends.

1.6.1 PROPOSED SYSTEM ADVANTAGES:

- Reduces Over fitting
- Works Well with Missing Data
- Handles Non-Linearity
- Resistant to Noise

CHAPTER 2

PROJECT DESCRIPTION

2.1 GENERAL:

This project to present a deep learning approach for detecting Neovascularization & Risk of macular edema. By using several deep learning layers for method creation to neovascularization detection. This technique will take Flask framework to make user interacted because to predict output without any doctor need.

2.2 METHODOLOGIES

2.2.1MODULES NAME:

MODULE:

- **Data Collection and Preprocessing Module**
- **Sales Forecasting Model (Random Forest Regression) Module**
- **Results Storage and Integration Module**
- **Data Visualization and Dashboard Module (Power BI)**
- **Business Insights and Optimization Module**

2.2.2 MODULES DESCSRIPTION:

1. Data Collection and Preprocessing Module:

Collecting historical sales data from various e-commerce platforms, including product details, transaction records, customer information, and external market trends.Cleaning the data by handling missing values, removing duplicates, and ensuring proper formatting. Performing feature extraction by analyzing product categories, sales trends, seasonal factors, and customer behavior. Encoding categorical data (e.g., product categories, region) using Label Encoding or One-Hot Encoding for compatibility with the Random Forest model. Splitting the dataset into training, validation, and test sets to ensure unbiased model evaluation.

2. Sales Forecasting Model (Random Forest Regression) Module:

Training the Random Forest Regression model on the preprocessed dataset to predict future sales. This includes:

Splitting the data into training and test sets.

Training the model on historical sales data to learn patterns, seasonality, and trends.

Evaluating the model using performance metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2.

Fine-tuning hyperparameters to reduce overfitting and improve model accuracy.

3. Results Storage and Integration Module:

Storing the predicted sales data in a structured format (e.g., CSV, Excel, or a database) for easy integration with visualization tools. Ensuring that the results are organized by time period (e.g., monthly or quarterly) and product-wise for easy analysis in Power BI.

4. Data Visualization and Dashboard Module (Power BI):

Creating interactive dashboards in Power BI to visualize the sales predictions and trends. The dashboard includes:

- Graphs showing actual vs. predicted sales over time.
- Sales trend analysis (e.g., monthly, quarterly).
- Seasonal fluctuations and product performance.
- Key performance indicators (KPIs) such as predicted revenue, best-selling products, and forecast accuracy.

5. Business Insights and Optimization Module:

Generating actionable business insights from the sales data using Power BI:

- Identifying products with high demand for inventory optimization.
- Detecting underperforming products for better marketing or discount strategies.
- Forecasting seasonal peaks for demand planning and resource allocation.
- Providing recommendations on inventory levels and product reordering based on predicted sales

2.3 TECHNIQUE USED OR ALGORITHM USED

2.3.1 EXISTING TECHNIQUE: -

- Decision Tree Regression is a type of supervised machine learning algorithm used to predict continuous numerical values by splitting data into subsets based on certain feature thresholds. Unlike classification, where the goal is to predict discrete categories, decision tree regression focuses on estimating continuous values. The algorithm works by constructing a tree-like model of decisions and their possible consequences. Each internal node of the tree represents a decision based on one of the input features, and each leaf node contains the predicted output, typically the average of the target variable in that region.
- This is done by choosing the feature and the threshold value that best separates the data points according to a chosen criterion, such as the mean squared error (MSE). Once the tree is constructed, predictions for new data points are made by following the path from the root to the appropriate leaf node, where the target value is returned.
- Decision tree regression is particularly useful when the relationship between the input variables and the target variable is non-linear or complex. It can capture intricate patterns in the data that simpler models like linear regression might miss.

2.3.2 PROPOSED TECHNIQUE USED OR ALGORITHM USED:

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- Random Forest Regression is widely used in sales forecasting, financial modeling, climate prediction, healthcare analytics, and other real-world applications due to its ability to handle large datasets, maintain high accuracy, and resist over fitting.
- Additionally, Power BI is used to create interactive dashboards that provide real-time insights into sales trends, customer behavior, and market demand. This visualization helps businesses monitor key performance indicators (KPIs), optimize inventory management, and make data-driven decisions. The system ensures better accuracy, scalability, and interpretability, making it a robust solution for e-commerce

CHAPTER 3

REQUIREMENTS ENGINEERING

3.1 GENERAL

We can see from the results that on each database, the error rates are very low due to the discriminatory power of features and the regression capabilities of classifiers. Comparing the highest accuracies (corresponding to the lowest error rates) to those of previous works, our results are very competitive.

3.2 HARDWARE REQUIREMENTS

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by software engineers as the starting point for the system design. It should what the system do and not how it should be implemented.

- PROCESSOR : DUAL CORE 2 DUOS.
- RAM : 4GB DD RAM
- HARD DISK : 250 GB

3.3 SOFTWARE REQUIREMENTS

The software requirements document is the specification of the system. It should include both a definition and a specification of requirements. It is a set of what the system should do rather than how it should do it. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the teams and tracking the team's progress throughout the development activity.

- Operating System : Windows 7/8/10
- Platform : Spyder3
- Programming Language : Python
- Front End : HTML, CSS

3.4 FUNCTIONAL REQUIREMENTS

A functional requirement defines a function of a software-system or its component. A function is described as a set of inputs, the behavior, Firstly, the system is the first that achieves the standard notion of semantic security for data confidentiality in attribute-based deduplication systems by resorting to the hybrid cloud architecture.

3.5 NON-FUNCTIONAL REQUIREMENTS

The major non-functional Requirements of the system are as follows

Usability

The system is designed with completely automated process hence there is no or less user intervention.

Reliability

The system is more reliable because of the qualities that are inherited from the chosen platform python. The code built by using python is more reliable.

Performance

This system is developing in the high level languages and using the advanced back-end technologies it will give response to the end user on client system with in very less time.

Supportability

The system is designed to be the cross platform supportable. The system is supported on a wide range of hardware and any software platform, which is built into the system.

Implementation

The system is implemented in web environment using Jupyter notebook software. The server is used as the intellignce server and windows 10 professional is used as the platform. Interface the user interface is based on flask provides server system.

CHAPTER 4

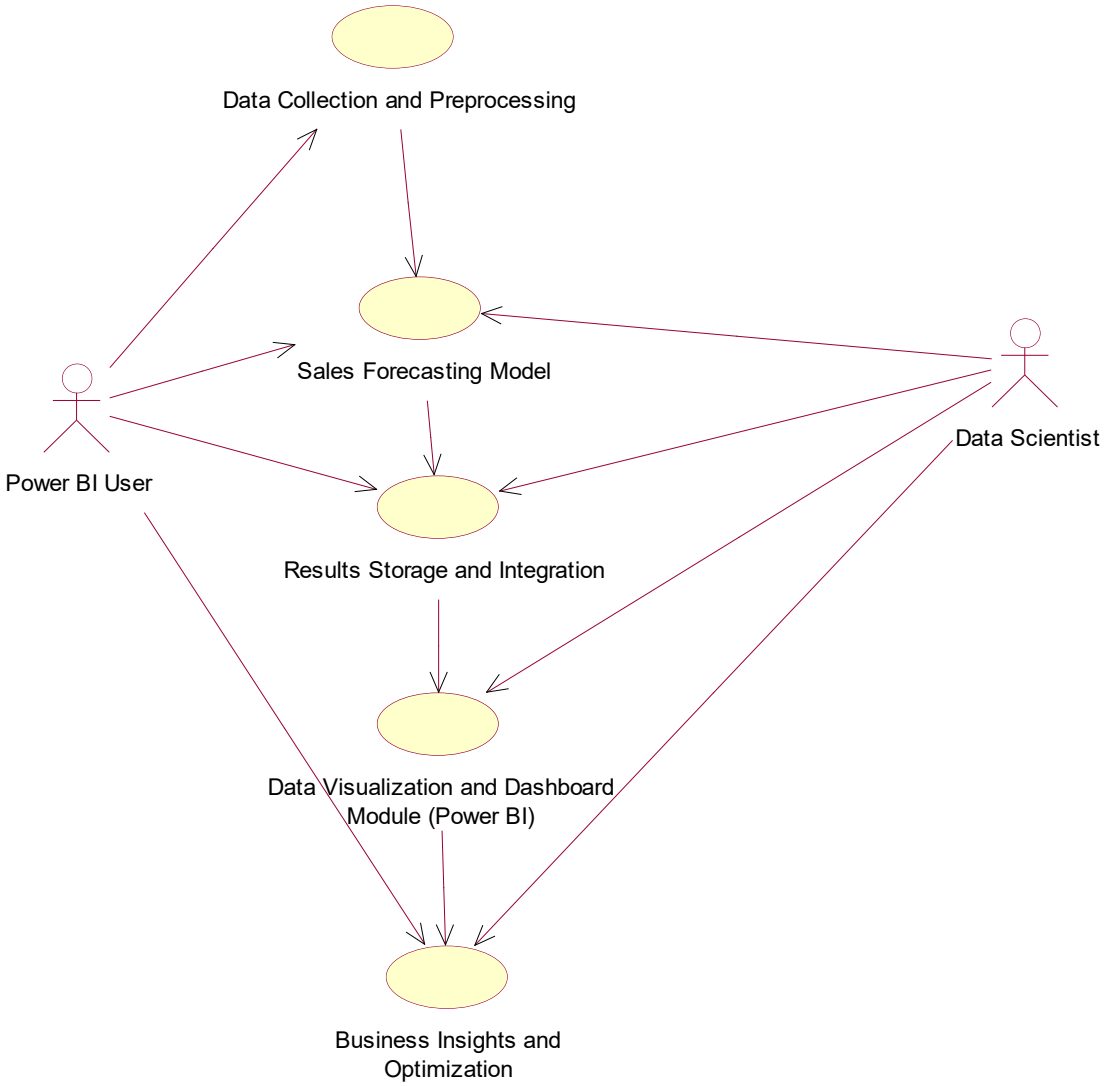
DESIGN ENGINEERING

4.1 GENERAL

Design Engineering deals with the various UML [Unified Modelling language] diagrams for the implementation of project. Design is a meaningful engineering representation of a thing that is to be built. Software design is a process through which the requirements are translated into representation of the software. Design is the place where quality is rendered in software engineering.

4.2 UML DIAGRAMS

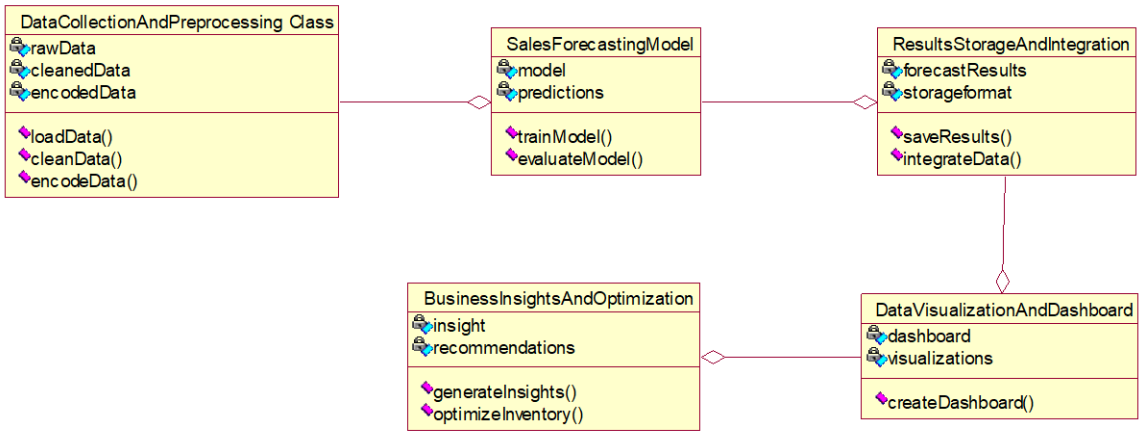
4.2.1 USE CASE DIAGRAM



EXPLANATION:

The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted. The above diagram consists of user as actor. Each will play a certain role to achieve the concept.

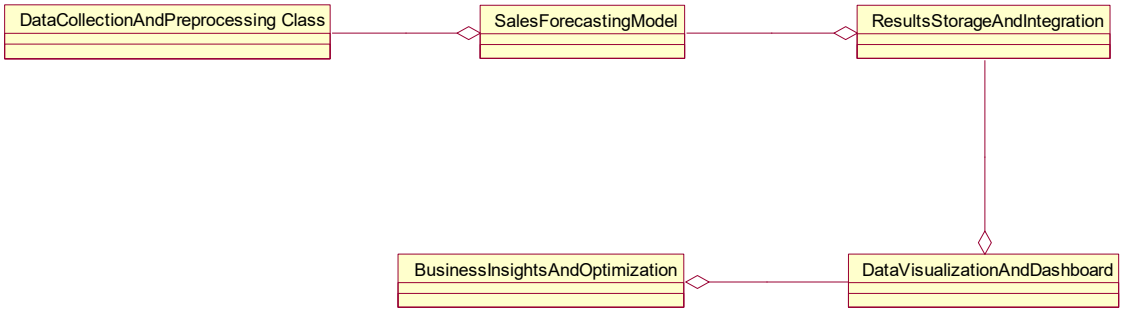
4.2.2 CLASS DIAGRAM



EXPLANATION

In this class diagram represents how the classes with attributes and methods are linked together to perform the verification with security. From the above diagram shown the various classes involved in our project.

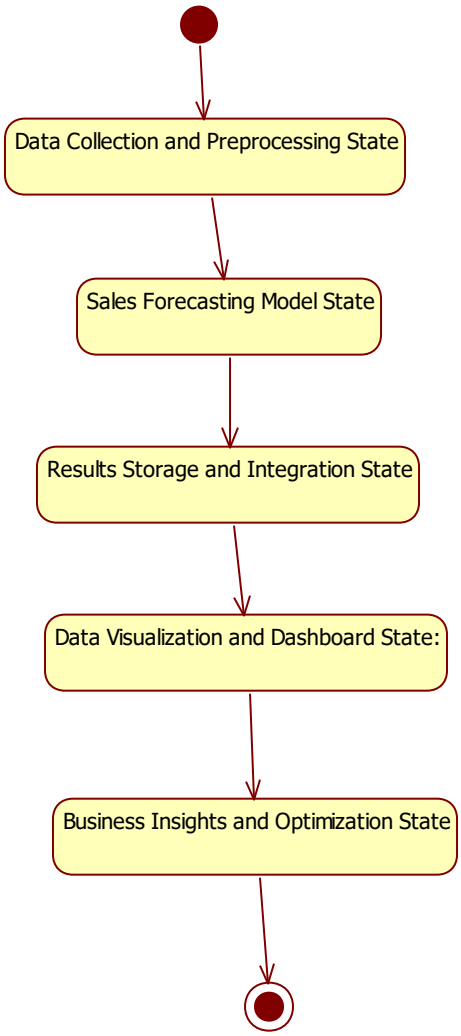
4.2.3 OBJECT DIAGRAM



EXPLANATION:

In the above digram tells about the flow of objects between the classes. It is a diagram that shows a complete or partial view of the structure of a modeled system. In this object diagram represents how the classes with attributes and methods are linked together to perform the verification with security.

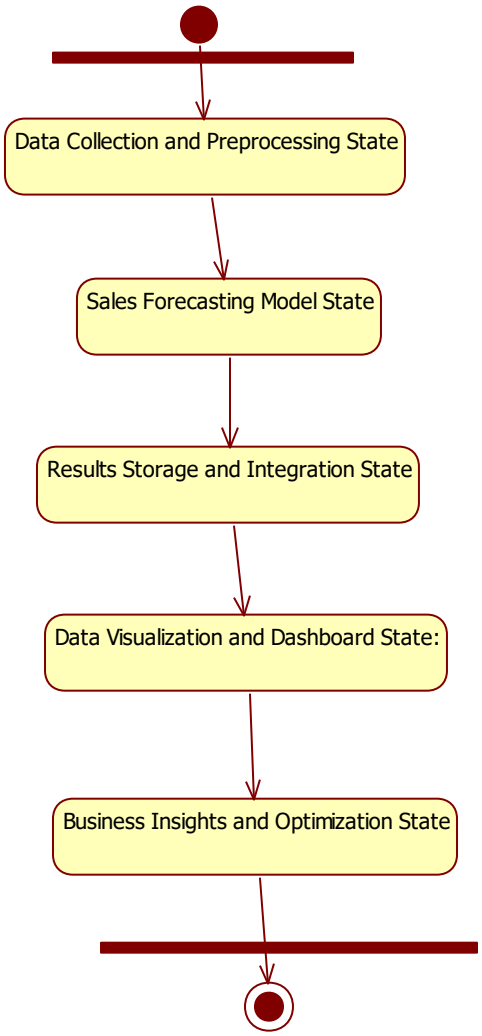
4.2.4 STATE DIAGRAM



EXPLANATION:

State diagram are a loosely defined diagram to show workflows of stepwise activities and actions, with support for choice, iteration and concurrency. State diagrams require that the system described is composed of a finite number of states; sometimes, this is indeed the case, while at other times this is a reasonable abstraction. Many forms of state diagrams exist, which differ slightly and have different semantics.

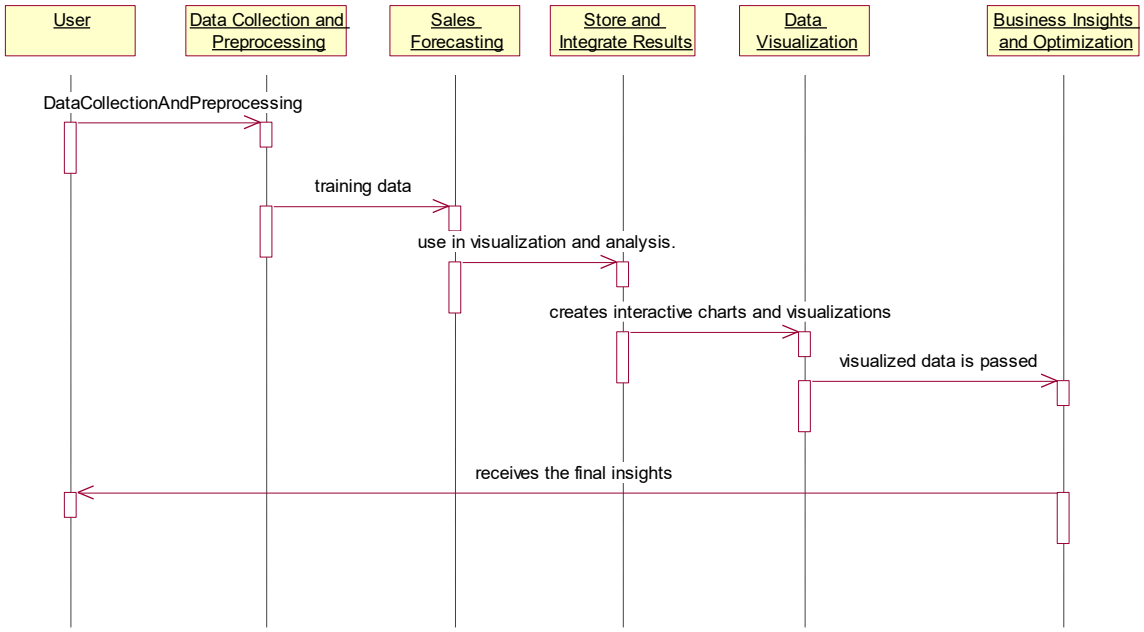
4.2.5 ACTIVITY DIAGRAM



EXPLANATION:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

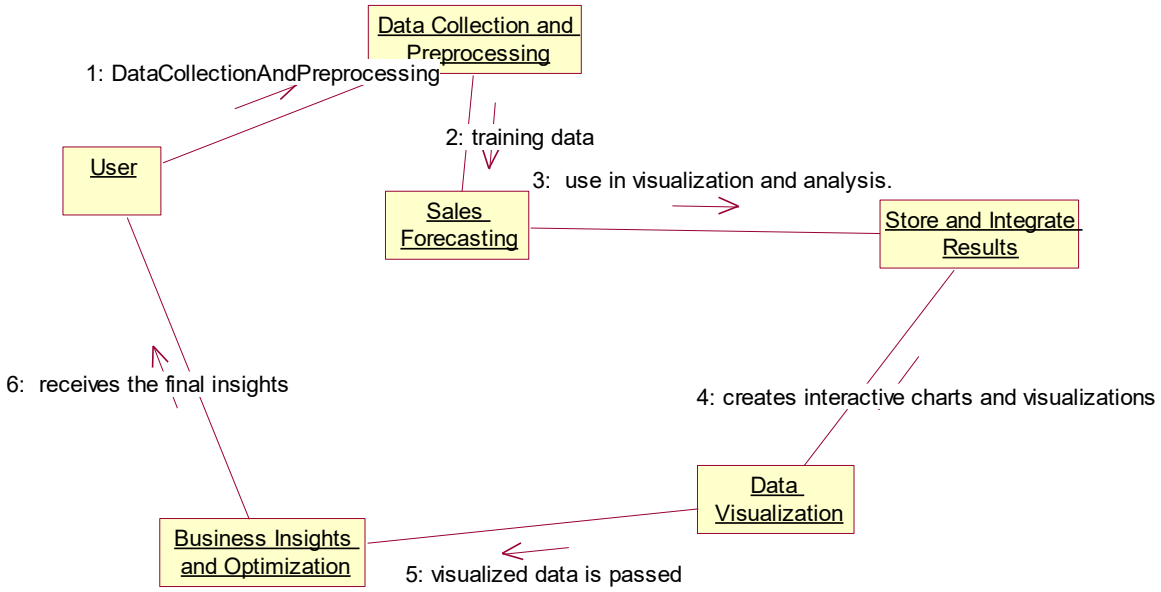
4.2.6 SEQUENCE DIAGRAM



EXPLANATION:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario.

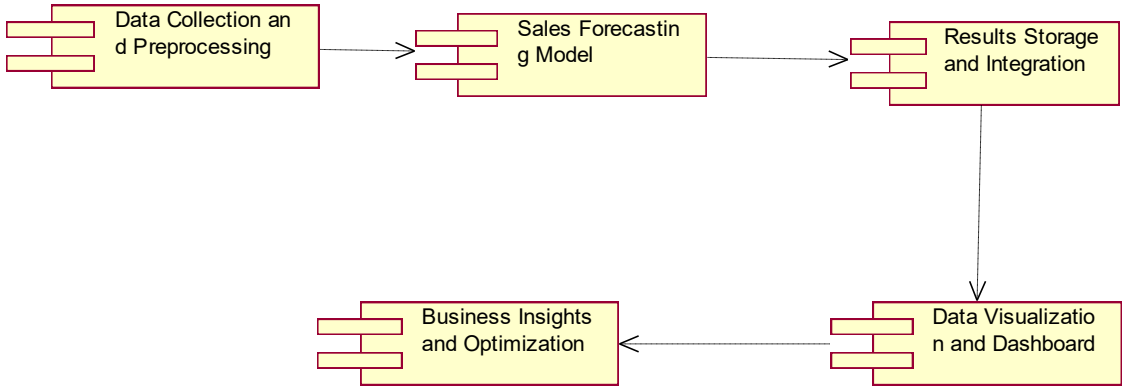
4.2.7 COLLABORATION DIAGRAM



EXPLANATION:

A collaboration diagram, also called a communication diagram or interaction diagram, is an illustration of the relationships and interactions among software objects in the Unified Modeling Language (UML). The concept is more than a decade old although it has been refined as modeling paradigms have evolved.

4.2.8 COMPONENT DIAGRAM

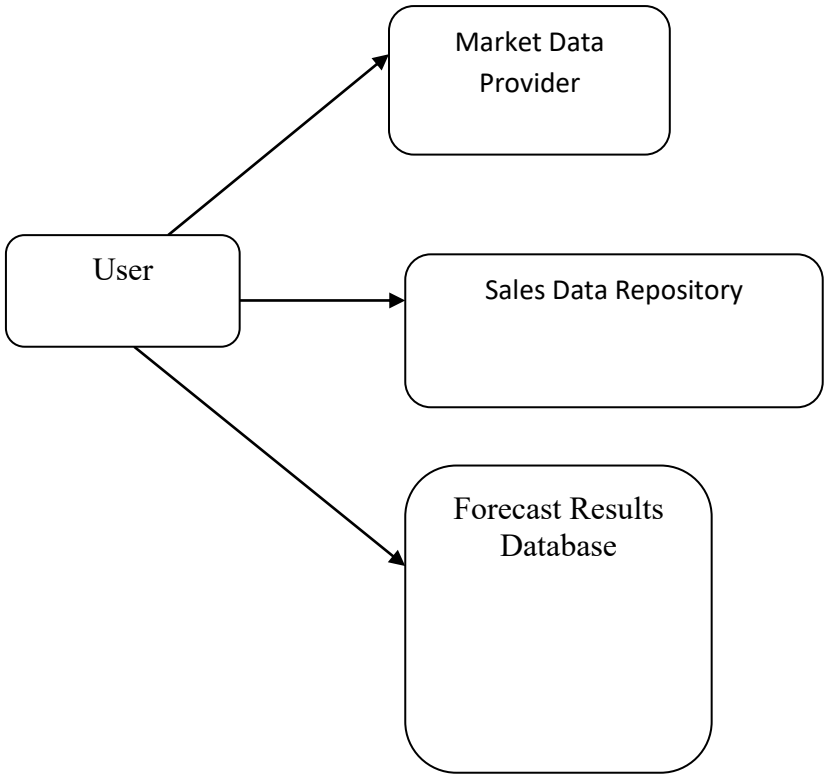


EXPLANATION

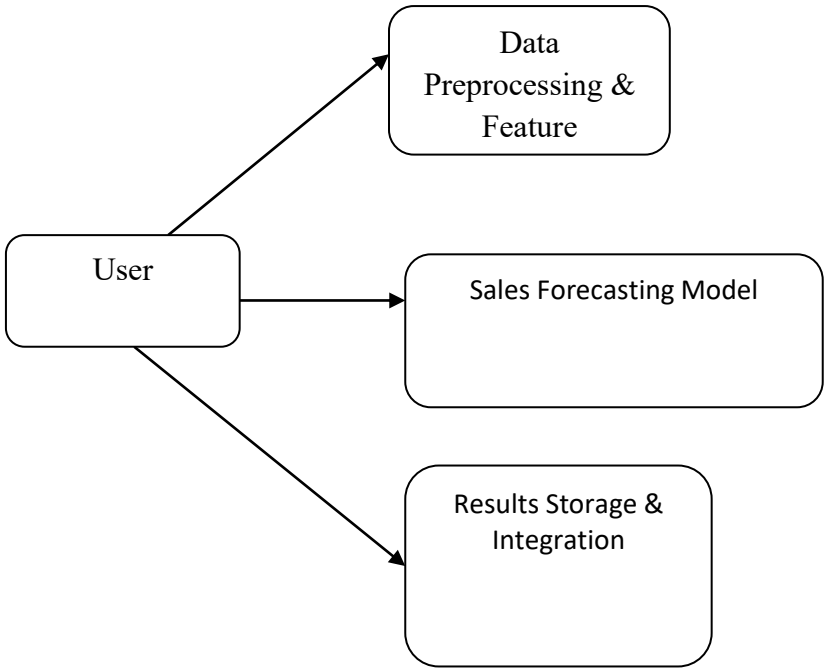
In the Unified Modeling Language, a component diagram depicts how components are wired together to form larger components and or software systems. They are used to illustrate the structure of arbitrarily complex systems. User gives main query and it converted into sub queries and sends through data dissemination to data aggregators. Results are to be showed to user by data aggregators. All boxes are components and arrow indicates dependencies.

4.2.9 Data Flow Diagram

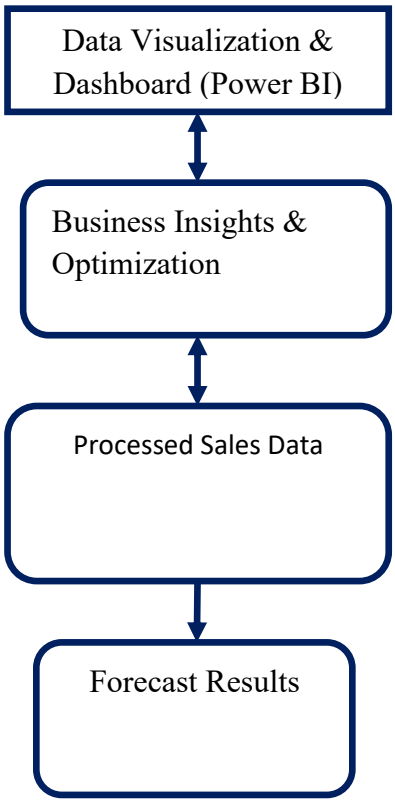
Level 0:



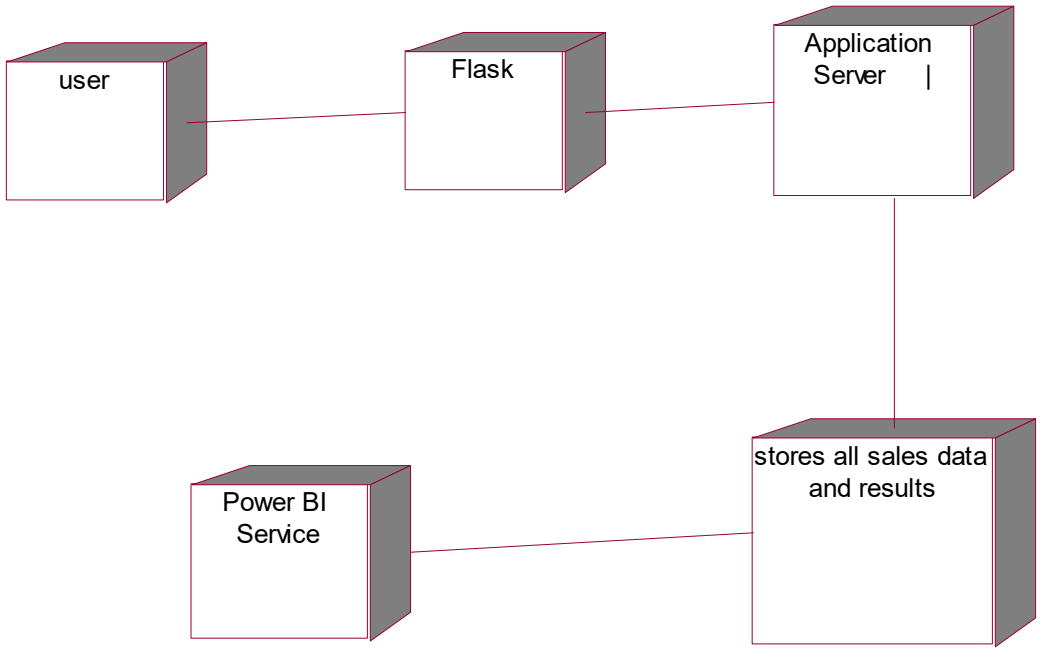
Level 1:


Data Preprocessing & Feature
User
Sales Forecasting Model
Results Storage & Integration

Level 2:


Data Visualization & Dashboard (Power BI)
Business Insights & Optimization
Processed Sales Data
Forecast Results

4.2.10 DEPLOYMENT DIAGRAM



EXPLANATION:

Deployment Diagram is a type of diagram that specifies the physical hardware on which the software system will execute. It also determines how the software is deployed on the underlying hardware. It maps software pieces of a system to the device that are going to execute it.

-

SYSTEM ARCHITECTURE:

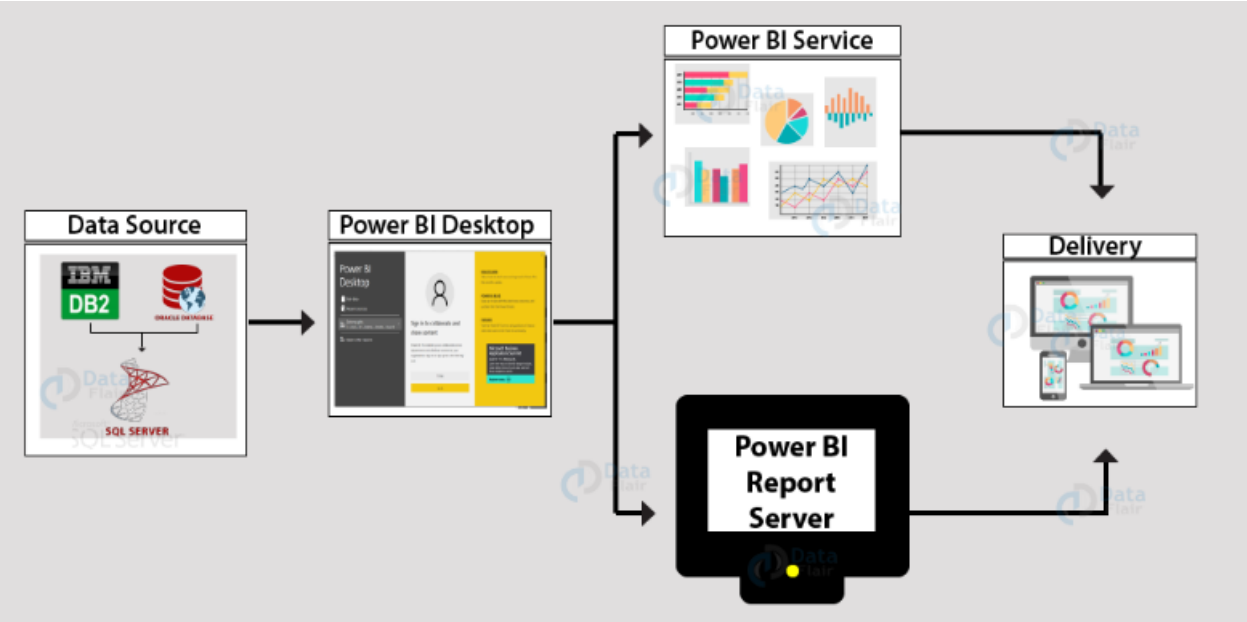


Fig 4.11: System Architecture

CHAPTER 5

DEVELOPMENT TOOLS

5.1 Python

Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It uses English keywords frequently where as other languages use punctuation, and it has fewer syntactical constructions than other languages.

5.2 History of Python

Python was developed by Guido van Rossum in the late eighties and early nineties at the National Research Institute for Mathematics and Computer Science in the Netherlands.

Python is derived from many other languages, including ABC, Modula-3, C, C++, Algol-68, SmallTalk, and Unix shell and other scripting languages.

Python is copyrighted. Like Perl, Python source code is now available under the GNU General Public License (GPL).

Python is now maintained by a core development team at the institute, although Guido van Rossum still holds a vital role in directing its progress.

5.3 Importance of Python

- **Python is Interpreted** − Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- **Python is Interactive** − You can actually sit at a Python prompt and interact with the interpreter directly to write your programs.
- **Python is Object-Oriented** − Python supports Object-Oriented style or technique of programming that encapsulates code within objects.

- **Python is a Beginner's Language** − Python is a great language for the beginner-level programmers and supports the development of a wide range of applications from simple text processing to WWW browsers to games.

5.4 Features of Python

- **Easy-to-learn** − Python has few keywords, simple structure, and a clearly defined syntax. This allows the student to pick up the language quickly.
- **Easy-to-read** − Python code is more clearly defined and visible to the eyes.
- **Easy-to-maintain** − Python's source code is fairly easy-to-maintain.
- **A broad standard library** − Python's bulk of the library is very portable and cross-platform compatible on UNIX, Windows, and Macintosh.
- **Interactive Mode** − Python has support for an interactive mode which allows interactive testing and debugging of snippets of code.
- **Portable** − Python can run on a wide variety of hardware platforms and has the same interface on all platforms.
- **Extendable** − You can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.
- **Databases** − Python provides interfaces to all major commercial databases.
- **GUI Programming** − Python supports GUI applications that can be created and ported to many system calls, libraries and windows systems, such as Windows MFC, Macintosh, and the X Window system of Unix.
- **Scalable** − Python provides a better structure and support for large programs than shell scripting.

Apart from the above-mentioned features, Python has a big list of good features, few are listed below −

- It supports functional and structured programming methods as well as OOP.
- It can be used as a scripting language or can be compiled to byte-code for building large applications.
- It provides very high-level dynamic data types and supports dynamic type checking.
- IT supports automatic garbage collection.
- It can be easily integrated with C, C++, COM, ActiveX, CORBA, and Java.

5.5 Libraries used in python

- numpy - mainly useful for its N-dimensional array objects.
- pandas - Python data analysis library, including structures such as dataframes.
- matplotlib - 2D plotting library producing publication quality figures.
- scikit-learn - the machine learning algorithms used for data analysis and data mining tasks.

Figure : NumPy, Pandas, Matplotlib, Scikit-learn

CHAPTER 6

IMPLEMENTATION

6.1 GENERAL

Coding:

```
from flask import Flask, render_template, request, redirect, url_for, session
import pickle
import numpy as np
import plotly.express as px
import pandas as pd  # Import pandas for handling CSV
import plotly.io as pio
import subprocess

app = Flask(__name__)
app.secret_key = 'your_secret_key'

# Load models
with open('models/sales_model1.pkl2', 'rb') as f:
    sales_model = pickle.load(f)

with open('models/profit_model2.pkl', 'rb') as f:
    profit_model = pickle.load(f)

with open('models/label_encoders2.pkl', 'rb') as f:
    encoders = pickle.load(f)

# Home Page (Login)
@app.route('/', methods=['GET', 'POST'])
def home():
    error = None
    if request.method == 'POST':
        username = request.form['username']
        password = request.form['password']
        if username == 'admin' and password == 'admin':
            session['user'] = username
            return redirect(url_for('predict'))
        else:
            error = 'Invalid Credentials'
```

```
    return render_template('home.html', error=error)

# Prediction Page
@app.route('/predict', methods=['GET', 'POST'])
def predict():

    predicted_sales = None
    profit_prediction = None

    if request.method == 'POST':
        try:
            # Get user input
            category_name = request.form['category_name']
            customer_region = request.form['customer_region']
            shipping_type = request.form['shipping_type']
            order_quantity = int(request.form['order_quantity'])
            days_scheduled = int(request.form['days_for_shipment_scheduled'])

            # Encode inputs
            cat = encoders['category_name'].transform([category_name])[0]
            region = encoders['customer_region'].transform([customer_region])[0]
            shipping = encoders['shipping_type'].transform([shipping_type])[0]

            input_data = np.array([[cat, region, shipping, order_quantity, days_scheduled]])

            # Predict sales
            predicted_sales = round(sales_model.predict(input_data)[0], 2)

            # Predict profit class
            profit_class = profit_model.predict(input_data)[0]
            profit_prediction = "Profitable ✅" if profit_class == 1 else "Not Profitable ❌"
        except Exception as e:
            predicted_sales = None
            profit_prediction = f"Error: {str(e)}"

    return render_template('predict.html',
                           predicted_sales=predicted_sales,
                           profit_prediction=profit_prediction)
@app.route('/visual', methods=['GET', 'POST'])
def chart():
    selected_region = request.form.get('region')
    selected_category = request.form.get('category')
    df = pd.read_csv("Ecommerce_data.csv", encoding='latin-1')
```

```
    # Apply filters if selected
    filtered_df = df.copy()
    if selected_region and selected_region != "All":
        filtered_df = filtered_df[filtered_df["customer_region"] == selected_region]
    if selected_category and selected_category != "All":
        filtered_df = filtered_df[filtered_df["category_name"] == selected_category]

    # Aggregate for bar chart: Total Sales by Category
    bar_data = filtered_df.groupby("category_name")["sales_per_order"].sum().reset_index()

    # Plotly bar chart
    fig = px.bar(
        bar_data,
        x="category_name",
        y="sales_per_order",
        title="Total Sales by Category (Filtered)",
        labels={"sales_per_order": "Total Sales", "category_name": "Category"},
        color="category_name"
    )
    fig.update_layout(xaxis_tickangle=-45)

    graph_html = pio.to_html(fig, full_html=False)

    # Dropdown values
    regions = ["All"] + sorted(df["customer_region"].dropna().unique())
    categories = ["All"] + sorted(df["category_name"].dropna().unique())

    return render_template("chart_filter.html", chart=graph_html, regions=regions, categories=categories,
                           selected_region=selected_region, selected_category=selected_category)

@app.route('/charts', methods=['GET', 'POST'])
def charts():  # ✅ Renamed function to avoid conflict
    df = pd.read_csv("Ecommerce_data.csv", encoding='latin-1')

    selected_region = request.form.get('region', 'All')
    selected_category = request.form.get('category', 'All')
    selected_chart = request.form.get('chart_type', 'Bar')

    if selected_region != 'All':
        df = df[df['customer_city'] == selected_region]

    if selected_category != 'All':
```

```
    df = df[df['category_name'] == selected_category]

# Group by city and category for bar charts
bar_data = (
    df.groupby(["customer_city", "category_name"])["sales_per_order"]
    .sum()
    .reset_index()
)

# Get top 10 cities by total sales
top_cities = (
    bar_data.groupby("customer_city")["sales_per_order"]
    .sum()
    .sort_values(ascending=False)
    .head(10)
    .index.tolist()
)
bar_data = bar_data[bar_data["customer_city"].isin(top_cities)]

# Chart rendering logic
if selected_chart == 'Bar':
    fig = px.bar(
        bar_data,
        x="customer_city",
        y="sales_per_order",
        color="category_name",
        title="Top 10 Cities by Sales (Grouped by Category)",
        labels={"sales_per_order": "Total Sales", "customer_city": "City", "category_name": "Category"},
        barmode='group'
    )
elif selected_chart == 'Pie':
    pie_data = (
        df.groupby("category_name")["sales_per_order"]
        .sum()
        .reset_index()
    )
    fig = px.pie(
        pie_data,
        names="category_name",
        values="sales_per_order",
        title="Sales Distribution by Category"
    )
elif selected_chart == 'Line':
    line_data = (
```

```
            df.groupby(["customer_city", "category_name"])["sales_per_order"]
            .sum()
            .reset_index()
        )
        fig = px.line(
            line_data[line_data["customer_city"].isin(top_cities)],
            x="customer_city",
            y="sales_per_order",
            color="category_name",
            title="Sales Trend by City and Category",
            markers=True
        )

    fig.update_layout(xaxis_tickangle=-45)
    graph_html = fig.to_html(full_html=False)

    city_list = ['All'] + sorted(df['customer_city'].dropna().unique().tolist())
    category_list = ['All'] + sorted(df['category_name'].dropna().unique().tolist())

    return render_template('index.html',
                           graph_html=graph_html,
                           city_list=city_list,
                           category_list=category_list,
                           selected_region=selected_region,
                           selected_category=selected_category,
                           selected_chart=selected_chart)

# Power BI paths
POWER_BI_PATH = r"C:\Program Files\Microsoft Power BI Desktop\bin\PBIDesktop.exe"
PBIX_FILE = r"C:\Users\madhu\OneDrive\Desktop\fail3\Ecommerce.pbix"

 # You'll create this next

@app.route('/open-powerbi')
def open_powerbi():
    # Check if the user is logged in before accessing this route
    # Redirect to login if the user is not logged in

    try:
        # Try to open the Power BI file using subprocess
        subprocess.Popen([POWER_BI_PATH, PBIX_FILE])
        # Render the template with a success message and a logout button
        return render_template('dashboard.html', message="✅ Power BI Dashboard is opening!")
```

```
    except Exception as e:
        # In case of an error, return the error message
        return f"❌ Error: {e}"

# Logout
@app.route('/logout')
def logout():
    session.pop('user', None)
    return redirect(url_for('home'))

if __name__ == "__main__":
    app.run(debug=True)
```

CHAPTER 7

SNAPSHOTS

General:

This project implements like application using python and the Server process is maintained using the SOCKET & SERVERSOCKET and the Design part is played by Cascading Style Sheet.

SNAPSHOTS

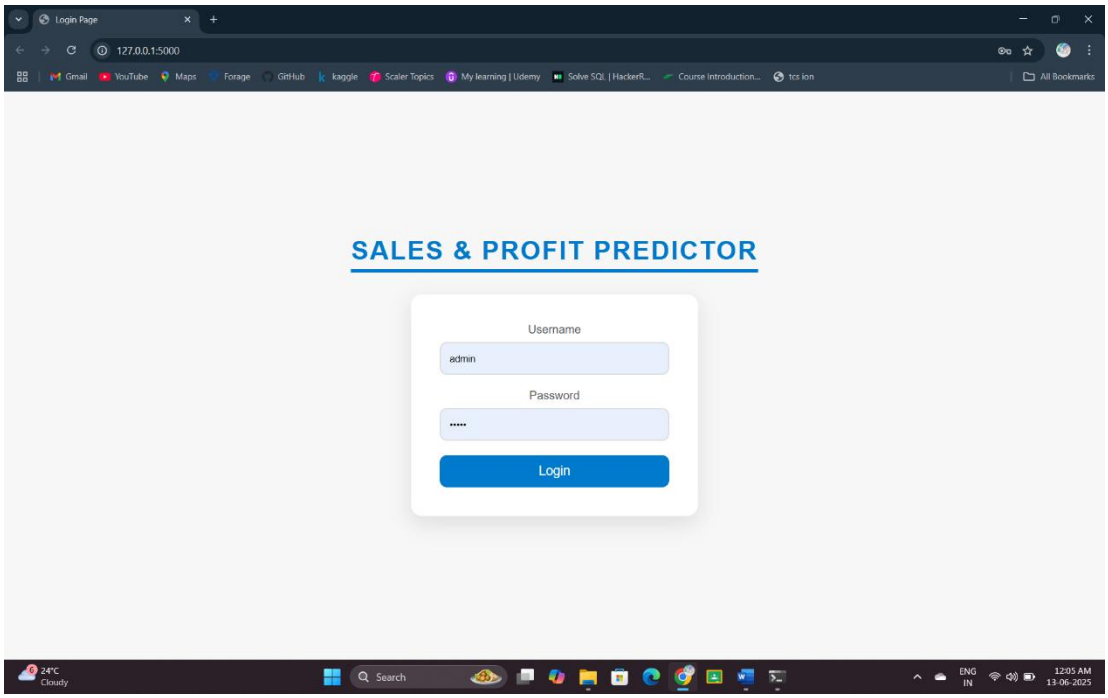


Fig1: login page

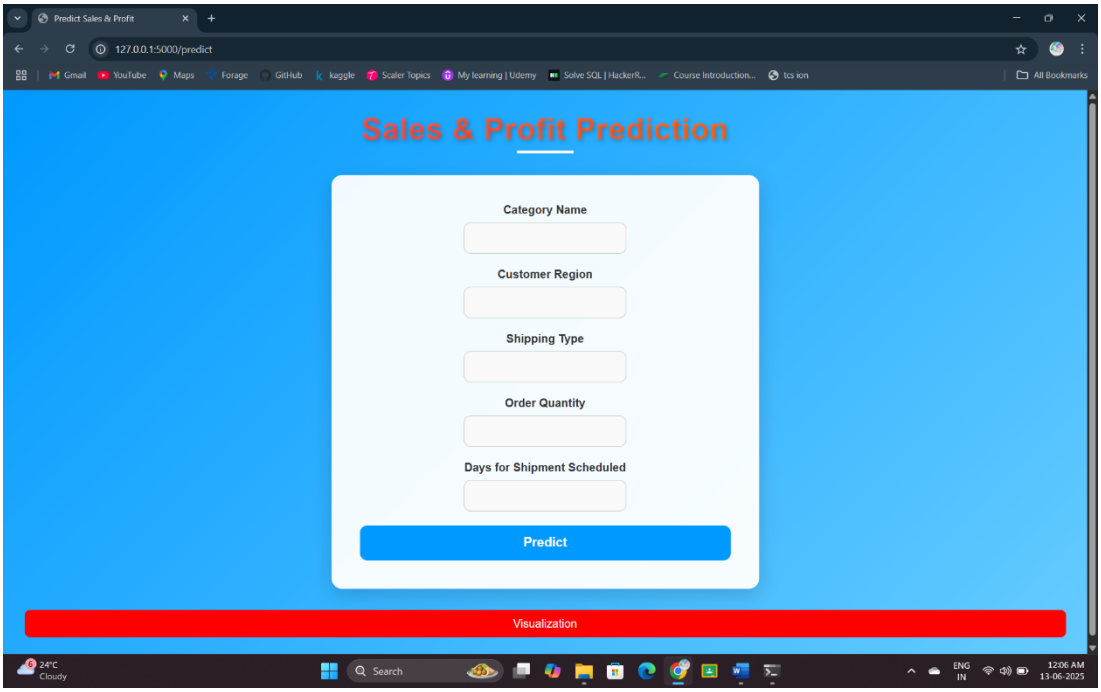
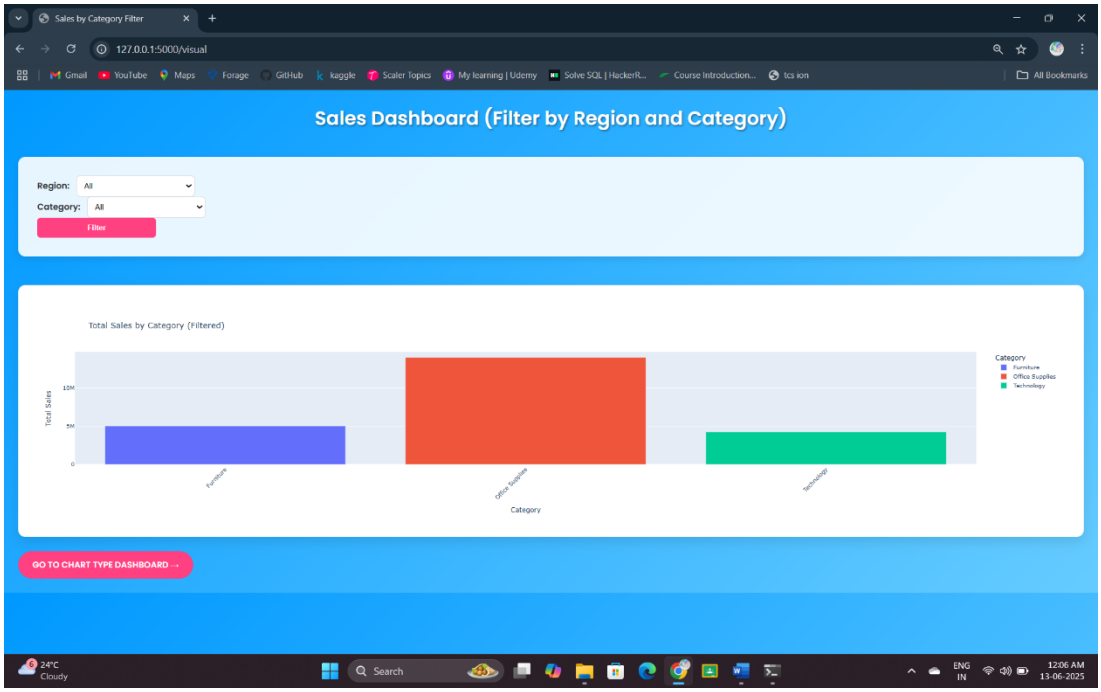


Fig2: prediction page



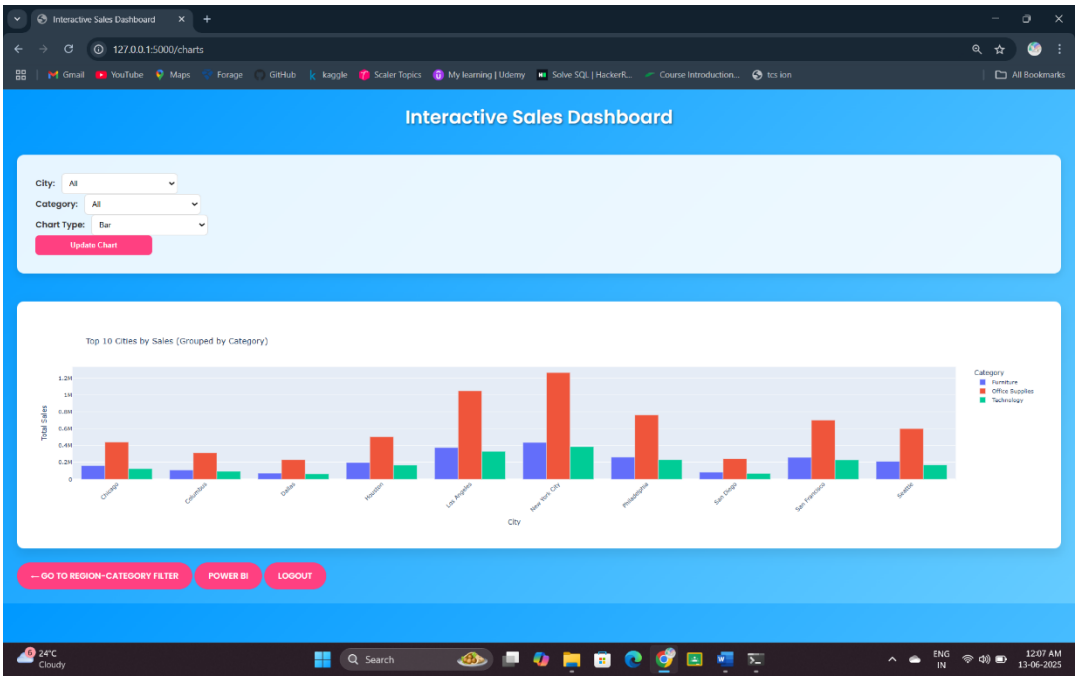
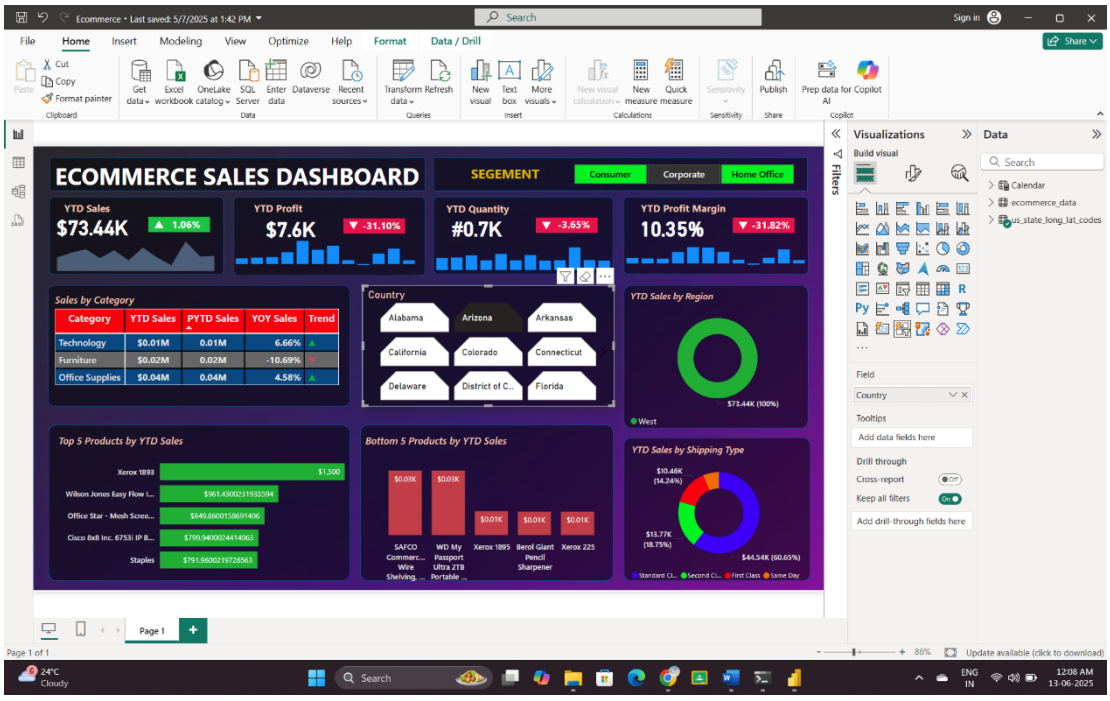


Fig3: Sales Dashboard



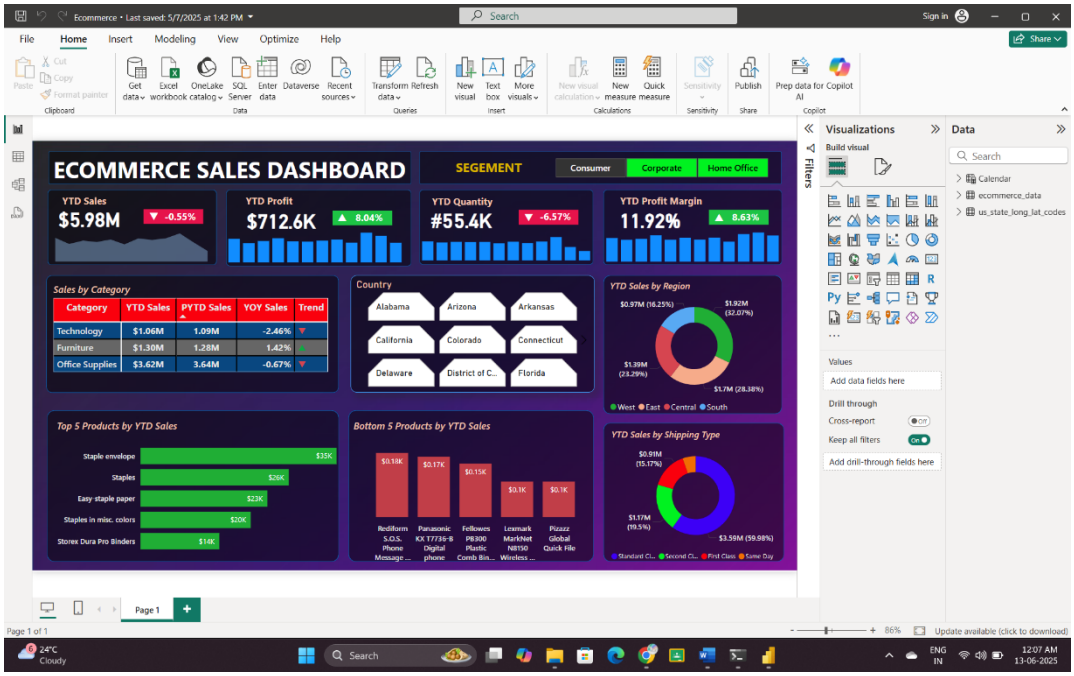


Fig4: Dashboard

CHAPTER 8
SOFTWARE TESTING

8.1 GENERAL

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

8.2 DEVELOPING METHODOLOGIES

The test process is initiated by developing a comprehensive plan to test the general functionality and special features on a variety of platform combinations. Strict quality control procedures are used. The process verifies that the application meets the requirements specified in the system requirements document and is bug free. The following are the considerations used to develop the framework from developing the testing methodologies.

8.3Types of Tests

8.3.1 Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program input produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

8.3.2 Functional test

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input : identified classes of valid input must be accepted.

Invalid Input : identified classes of invalid input must be rejected.

Functions : identified functions must be exercised.

Output : identified classes of application outputs must be exercised.

Systems/Procedures: interfacing systems or procedures must be invoked.

8.3.3 System Test

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

8.3.4 Performance Test

The Performance test ensures that the output be produced within the time limits,and the time taken by the system for compiling, giving response to the users and request being send to the system for to retrieve the results.

8.3.5 Integration Testing

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects.

The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

8.3.6 Acceptance Testing

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Acceptance testing for Data Synchronization:

- The Acknowledgements will be received by the Sender Node after the Packets are received by the Destination Node
- The Route add operation is done only when there is a Route request in need
- The Status of Nodes information is done automatically in the Cache Updation process

8.2.7 Build the test plan

Any project can be divided into units that can be further performed for detailed processing. Then a testing strategy for each of this unit is carried out. Unit testing helps to identity the possible bugs in the individual component, so the component that has bugs can be identified and can be rectified from errors.

CHAPTER 9

FUTURE ENHANCEMENT

9.1 FUTURE ENHANCEMENTS

In the future, the AI-powered sales forecasting system can be enhanced by integrating real-time data streams to enable dynamic and continuously updating forecasts. This would allow businesses to respond instantly to changes in customer behavior and market conditions. Additionally, incorporating advanced machine learning models such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU) could further improve the accuracy of time-series predictions. The system could also be extended with AI-based recommendation engines to suggest inventory restocking strategies and personalized product suggestions. Integrating external data sources like competitor pricing, market trends, and social media sentiment can enrich the forecasting model and provide more holistic insights. Moreover, making the Power BI dashboards mobile-responsive or building a dedicated mobile app would allow users to access critical business insights on the go. Lastly, the addition of automated alerts and scheduled reports can help decision-makers stay informed about significant changes or anomalies in sales trends.

CHAPTER 10

CONCLUSION AND REFERENCES

10.1 CONCLUSION

The AI-Powered Sales Forecasting and Dashboard Analytics system provides a robust and intelligent solution for e-commerce businesses to predict sales trends and make informed decisions. By leveraging Random Forest Regression and Power BI, the system delivers accurate sales forecasts, interactive dashboards, and actionable insights. This not only enhances inventory management and resource allocation but also supports data-driven decision-making, ultimately leading to increased efficiency and profitability. The system's modular design allows for future scalability and integration with more advanced analytics tools and real-time data sources, ensuring long-term business adaptability and growth.

10.2 REFERENCES

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