A

MINI PROJECT REPORT

ON

RETAIL EDGE

Submitted in partial fulfillment of the requirements
For the award of Degree of

BACHELOR OF ENGINEERING

IN

CSE (Artificial Intelligence & Machine Learning)

Submitted By

N.V.S.TEJASWI **245322748106**

Under the guidance

Of

Dr. T. SWATHI PRIYADARSHINI

ASSISTANT PROFESSOR

Department of CSE(AIML)

NEIL GOGTE INSTITUTE OF TECHNOLOGY

Kachavanisingaram Village, Hyderabad, Telangana 500058.

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NEIL GOGTE INSTITUTE OF TECHNOLOGY

A Unit of Keshav Memorial Technical Education (KMTES)
Approved by AICTE, New Delhi & Affiliated to Osmania University, Hyderabad

CERTIFICATE

This is to certify that the project work (PW533CSM) entitled "**RETAIL EDGE"** *is a bonafide work carried out by* **N.V.S.TEJASWI (245322748106)** of III-year V semester **Bachelor of Engineering** *in* **CSE (Artificial Intelligence & Machine Learning)** *by Osmania University, Hyderabad during the academic year* **2022-2026** *is a record of bonafide work carried out by them. The results embodied in this report have not been submitted to any other University or Institution for the award of any degree*

Internal Guide

Dr. T. Swathi Priyadarshini
Assistant Professor

Head of Department

Dr. K. Vinuthna Reddy
Associate Professor

External

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DECLARATION

We hereby declare that the Mini Project Report entitled, "**RETAIL EDGE**" submitted for the B.E degree is entirely our work and all ideas and references have been duly acknowledged. It does not contain any work for the award of any other degree.

Date:

N. V. S. Tejaswi

(245322748106)

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ABSTRACT

The **Retail Edge** project introduces an advanced solution to transform retail operations in the existing system. This system aims to address inefficiencies in traditional retail processes, such as contextless searches, limited personalization, and fragmented data analysis.

The platform provides tailored functionalities for three primary user groups: customers, associates, and mart owners. Customers benefit from intuitive product searches and personalized recommendations, enhancing their shopping experience. Associates gain actionable insights into sales trends and stock availability, enabling them to optimize retail operations. Mart owners can access consolidated performance data across branches, empowering strategic decision-making.

Designed for scalability and reliability, the system employs Streamlit for an intuitive front-end, Python for the back-end, MongoDB for secure data management, and a RAG-enhanced chatbot for enhanced interaction. The Retail Query System offers a user-friendly, secure, and efficient solution that simplifies retail operations, improves customer satisfaction, and fosters business growth.

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INTRODUCTION

1.1 PROBLEM STATEMENT

In the fast-paced world of retail, businesses generate a lot of data every day. This data comes from many places like sales transactions, customer feedback, and inventory logs. Analyzing this data to find useful insights is essential for making smart decisions and staying ahead of the competition. However, traditional methods often struggle to handle the vast and varied data, especially unstructured data like customer reviews.

Recent advancements in artificial intelligence (AI) and natural language processing (NLP) have introduced new ways to analyze data. Implementation of RAG(Retrieval Augmented Generation), can understand and generate human-like text. This makes them perfect for analyzing unstructured data and finding valuable insights. By using RAG implementation retail businesses can transform their raw data into meaningful information that drives better decisions and improves operations.

This project aims to create a powerful retail data analysis system using a large language model. The system will analyze different types of retail data, including sales trends, customer preferences, product performance, and inventory management. By using advanced NLP techniques, the system will offer a user-friendly interface for businesses to explore their data, spot patterns, and make data-driven decisions.

1.2 MOTIVATION

The motivation for this project stems from the increasing demand for intelligent, data-driven solutions in the retail sector. By integrating cutting-edge technology such as RAG (Retrieval-Augmented Generation), we aim to:

1. Provide a seamless and personalized shopping experience for customers.
2. Empower sales associates with actionable insights into stock and sales trends.

3. Enable mart owners to visualize financial data comprehensively and make informed strategic decisions.
4. Bridge the gap between manual and automated processes, ensuring scalability and operational excellence.
5. Foster growth and profitability by leveraging AI to streamline retail operations.

1.3 SCOPE

The project focuses on developing a unified platform with three distinct user interfaces:

- **Customer Interface:**
    - Advanced search capabilities with contextual understanding.
    - Personalized product recommendations based on customer behaviour.
- **Associate Interface:**
    - Branch-wise data visualization for stock and sales trends.
    - Tools for identifying and addressing underperforming products.
- **Owner Interface:**
    - Comprehensive data consolidation across branches.
    - Visualization of overall financial performance.
    - Integration of a RAG-implemented chatbot for retail-specific queries.

The platform a separate dataset for training the RAG model. Streamlit will be employed for creating a user-friendly interface, and Astra DB will manage data storage and retrieval.

1.4 OUTLINE

- **Introduction:**
  - Overview of the current challenges in the retail sector.
  - Introduction to RAG, AI technologies and their relevance to this project.
- **Proposed Solution:**
  - Description of the platform's architecture in the domain of retail.
  - Key features of the customer, associate, and owner interfaces.
- **Implementation Details:**
  - Datasets used: Amazon Customer Reviews and a retail salesman dataset.
  - Algorithms and technologies: Gemini, Streamlit, and Astra DB.
  - Workflow: Data preprocessing, training, and deployment.
- **Use Cases and Benefits:**
  - Real-world scenarios demonstrating improved customer satisfaction, sales insights, and strategic decision-making.
- **Conclusion:**
  - Summary of the project's impact on the retail sector.
  - Future enhancements, such as adding multi-language support and expanding to other domains.

CHAPTER-2

LITERATURE SURVEY

2.1 EXISTING SYSTEM

The current retail systems would allow customer interactions to happen through old-fashioned search engines that possess prior preemptive keyword-based queries with which it does not comprehend the context of searches. This becomes a lot of product discovery inefficiency, irrelevant results, and frustrating encounters for a customer. Personalized recommendations are generally common and quite unresponsive to the new, real-time changes in preferences among customers.

Disadvantages:

- The salespeople rely on static reports that give insight but no real-time analysis. Therefore, it can be quite tough to act fast enough to capitalize on changes when something new pops up in trends, underperforming products, and shifting customer behaviors.
- The owners of the mart find it challenging to rely on the outdated methods, which particularly impede their reliance on real-time analysis of many important financial performances such as inventory turnover and sales metrics. This leads to later decisions and resultant lower operational efficiencies.

Hence, such limitations will not support optimizing retail operations and providing a frictionless shopping experience. These issues can be resolved through the integration of AI technology, which proposes smarter, real-time search capabilities, dynamic sales insights, and combined financial analysis across branches to help retailers better manage the expectations of customers and improve decision-making.

2.2 PROPOSED SYSTEM:

Our Retail Edge system integrates frontier technologies to empower enriched customer, associate, and owner experiences on a strong, scalable MERN-stack-built platform. This system combines advanced NLP, retrieval-augmented generation (RAG), and analytics to deliver an intelligent seamless retail experience.

Advantages:

- **Customer Experience:** By using advanced filtering algorithms and sophisticated NLP, the output about any product under search would be correct for the customer. Continuous collection and processing of feedback further augment the machine.
- **Associate Tools:** The associate user interface will enable data visualization by branch in addition to an overview, so the associate can quickly see trends and performance at specific retail units. It will allow informed decision-making with rich sales views.
- **Owner Dashboard:** A comprehensive dashboard provides detailed business analysis and strategic insights, leveraging RAG for data-driven decision-making based on customer feedback.
- **Chatbot Integration:** Our system seamlessly combines RAG and NLP to enhance the output of the chatbot, serving accurate, contextually relevant responses by referencing an external knowledge base without retraining. The architecture is used by this chatbot to fetch relevant information from the vector store, so it can provide very high precision context-aware answers. Continuous feedback loops help improve the system over time, so it will stay responsive, scalable, and user-friendly.

Overall, this proposed solution provides a scalable, high-performance solution for complex retail queries, with user satisfaction at the maximum.

CHAPTER-3

SOFTWARE REQUIREMENTS SPECIFICATION

3.1 OVERALL DESCRIPTION

This SRS outlines the comprehensive framework of RETAIL EDGE project. It details the system's functionalities, interfaces, and operational requirements, serving as a reference for stakeholders and developers. Key objectives include delivering personalized customer experiences, providing actionable insights for associates, and enabling mart owners to make informed decisions through advanced analytics.

3.2 OPERATING ENVIRONMENT

Software Requirements

Operating System : Windows 10

Front-end : HTML, CSS, JavaScript,Streamlit.

Back-end : Python

Database : MongoDB, Astra DB

Server : Flask (Web Framework)

Development Kit : Visual Studio Code (Latest Version)

Hardware Requirements

Processor : Intel Core i5 (Min)

Speed : 2.5 GHz (Min)

RAM : 8 GB (Min)

Hard Disk : 10 GB (Min)

3.3 FUNCTIONAL REQUIREMENTS

User Registration/Login:

Users can create accounts and log in to save their previous data.

Chatbot:

- Enable interaction with a chatbot to provide retail strategy insights.
- The user can ask any query and the bot will answer appropriately.
- The history of the chat will be displayed.

Visualization:

- Users can upload a .csv file , which will be visualized as a graph.

Product Recommendation:

- The user may enter the product they want to search.
- It gives top 5 products with their details.
- The user will be redirected to the product page upon clicking on the URL provided.

3.4 NON-FUNCTIONAL REQUIREMENTS

3.4.1 Performance Requirements

Performance requirements pertain to the expected operational metrics of the RETAIL EDGE.

Response Time:

The system shall deliver the output within 5 seconds of input processing.

Recovery Time:

In the event of a system failure, recovery mechanisms shall restore the service within 10 seconds, with an average repair time of less than 20 minutes.

Start-Up/Shutdown Time:

The platform shall be fully operational within 2 minute of startup and shall shut down gracefully in under 30 seconds.

Capacity:

The system shall support up to 1000 concurrent users without any degradation in response time or accuracy.

Utilization of Resources:

The system shall maintain a storage limit of 1 lakh processed user records. If this limit is exceeded, older records shall be archived and removed from active storage to maintain performance.

3.4.2 Safety Requirements

--NA--

3.4.3 Security Requirements

- The system shall require secure user authentication to ensure that only authorized users can access the personalized recommendation services.
- User data shall be encrypted during transmission and storage to prevent unauthorized access.
- Data processing shall occur on secure servers with restricted access to maintain privacy.
- User data will not be shared with third parties.

3.4.4 Software Quality Attributes

Reliability:

The system shall implement failover mechanisms, ensuring continuous operation by switching to a backup server if the primary server fails.

Availability:

The system shall be accessible 24/7, ensuring uninterrupted service for users at any time.

Security:

Every user will be assigned a unique and secure ID for accountability and data protection.

Maintainability:

The platform will be designed with a modular architecture and will include detailed documentation to facilitate regular updates, bug fixes, and the addition of new features.

Usability:

User interfaces shall be intuitive, visually appealing, and optimized for accessibility, allowing individuals of varying technical expertise to easily interact with the system.

Scalability:

The system will be designed to support future enhancements, including such as new data visualization methods or chatbot capabilities or integrating real time sales.

CHAPTER-4

DESIGN DIAGRAMS

4.1 UML DIAGRAMS

4.1.1 Use-Case Diagram

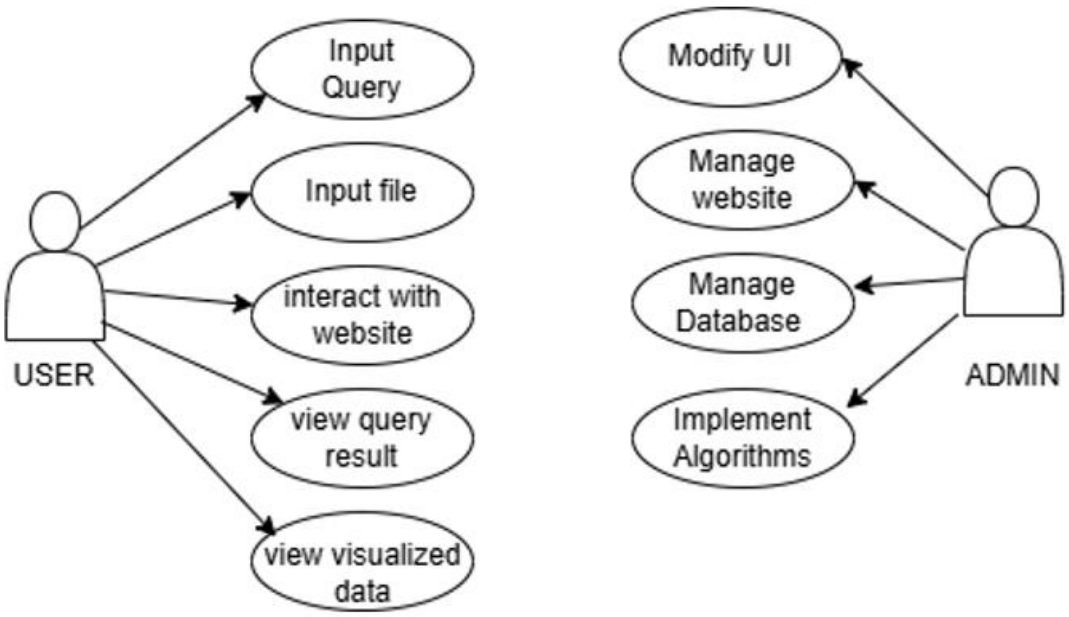

Fig.4.1: Use Case Diagram

Description:

User Role:

- Input Query: Users can submit queries to the system.
- Input File: Users have the ability to upload files to the system.
- Interact with Website: Users can interact with various features and functionalities of the website.
- View Query Results: After submitting a query, users can see the results generated by the system.

- View Visualized Data: Users can access and view data presented in a visualized format, such as graphs or charts.

Admin Role:

- Modify UI: Admins can make changes to the website's user interface.
- Manage Website: Admins oversee the overall functionality and maintenance of the website.
- Manage Database: Admins handle database management tasks, such as updating or maintaining data.
- Implement Algorithms: Admins are responsible for integrating and managing algorithms used by the system.

4.1.2 Class Diagram

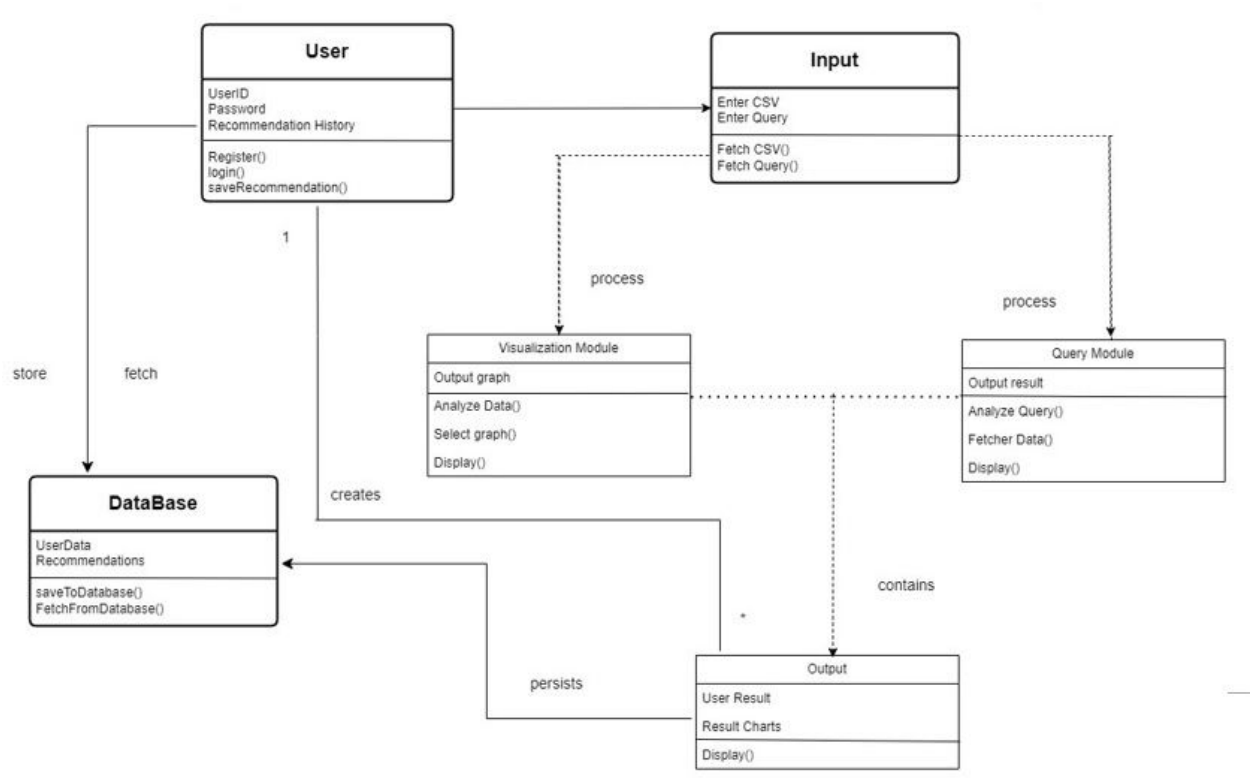

Fig.4.2: Class diagram for Application.

Description:

User:

- Attributes: UserID, Password, Recommendation History.
- Methods: Register, Login, Save Recommendations.
- Interacts with the database and provides input.

Input:

- Attributes: Enter CSV, Enter Query.
- Methods: Fetch CSV, Fetch Query.
- Processes data through modules.

Visualization Module:

- Outputs graphs by analyzing data and display the graph.

Query Module:

- Processes user queries and fetches relevant data for display.

Output:

- Contains user results and result charts, displayed to the user.

Database:

- Stores and retrieves user data and recommendations.

4.1.3 Sequence Diagram

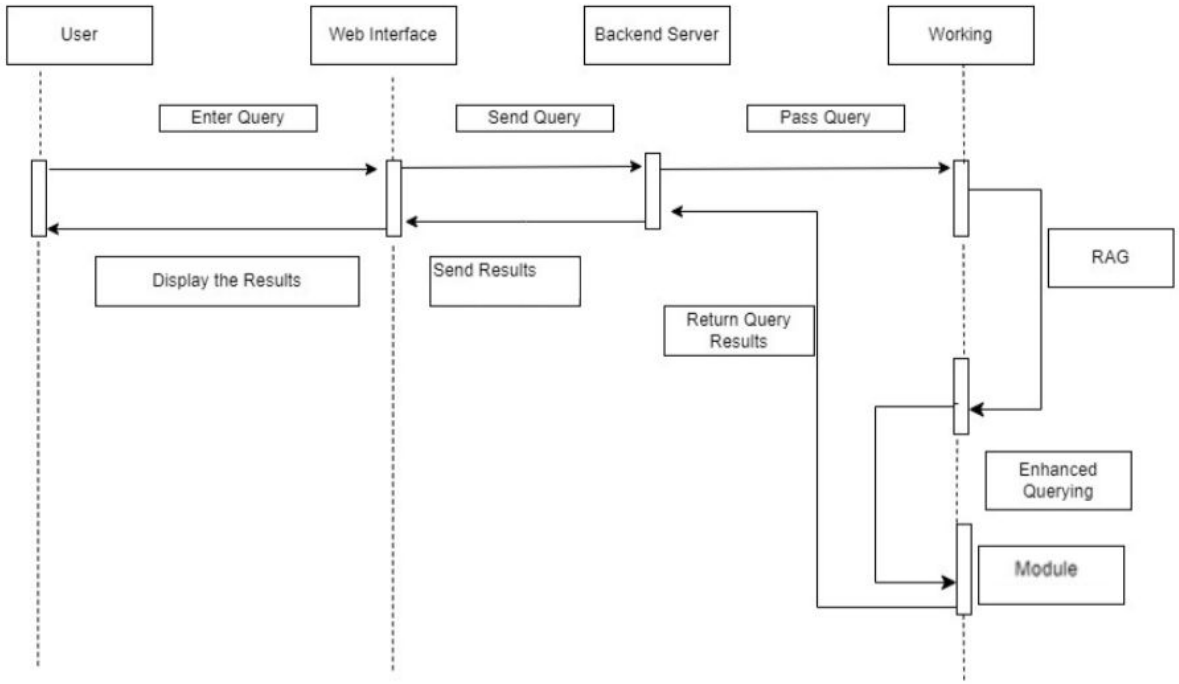

Fig4.3.1: Sequence Diagram for Query Model.

Description:

1. **User Interaction**:
    - The process begins with the user the query via the Web Interface.
2. **Web Interface Processing**:
    - Upon receiving the query, the Web Interface sends it to the Backend Server for further processing.

3. **Backend Server Processing**:
    - The Backend Server receives the query and passes it to the Working Module, which includes the bot and RAG
    - The server ensures the query is properly handled, formatted, and forwarded for analysis.
4. **Working Module Execution**:
    - The query is first enhanced by the RAG model.
    - The bot analyzes the enhanced query to give appropriate answer.
    - The results are passed to the Query Module, which prepares the data for presentation.
5. **Query Module**:
    - The output data is sent back to the Backend Server.
6. **Results Delivery**:
    - The Backend Server forwards the query results to the Web Interface, which displays them to the user.

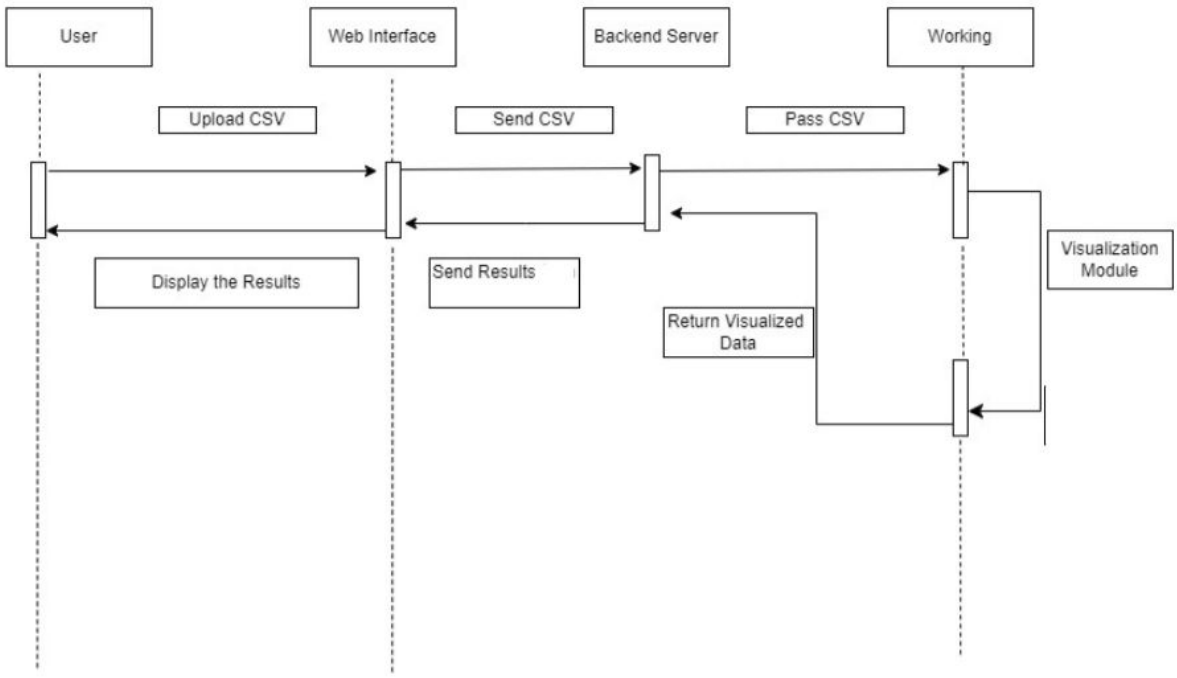

Fig4.3.2: Sequence Diagram for Visualization Model

Description

7. **User Interaction**:
    - The process begins with the user uploading a CSV file via the Web Interface.
    - This CSV file contains the required data (e.g., sales, inventory, or customer details) for processing.
8. **Web Interface Processing**:
    - Upon receiving the uploaded file, the Web Interface sends the CSV file to the Backend Server for further processing.

9. **Backend Server Processing**:
    - The Backend Server receives the CSV and passes it to the Working ModuleThe server ensures the file is properly handled, formatted, and forwarded for analysis.
10. **Working Module Execution**:
    - The CSV is passed to the Visualization Module, which prepares the data for presentation.
11. **Visualization Module**:
    - The output data is sent back to the Backend Server.
12. **Results Delivery**:
    - The Backend Server forwards the visualized results to the Web Interface, which displays them to the user.

CHAPTER-5

IMPLEMENTATION

5.1 SAMPLE CODE

CHAT BOT

```
import streamlit as st

from cassandra.cluster import Cluster

from cassandra.io.asyncorereactor import AsyncoreConnection

import os

from getpass import getpass

from datasets import load_dataset

from langchain_astradb import AstraDBVectorStore

from langchain.embeddings import OpenAIEmbeddings

from langchain.schema import Document

from langchain.prompts import ChatPromptTemplate

from langchain.chat_models import ChatOpenAI

from langchain.schema.output_parser import StrOutputParser

from langchain.schema.runnable import RunnablePassthrough


# Streamlit app starts here

st.title("Financial Data Query App")
```

```
# Enter your settings for Astra DB and Open:

os.environ["ASTRA_DB_API_ENDPOINT"] = "https://09ca6820-98c6-4323-8fc9-027882b78b92-us-east-2.apps.astra.datastax.com"

os.environ["ASTRA_DB_APPLICATION_TOKEN"] = "AstraCS:qWPOLaUdNGEUlqFCeExOYYPC:859aca1597224d735b3c054b879c9e1190429177b6cf3418e78bd4ee246e599d"

os.environ["KEY"] = ""


# Ensure the environment variables are correctly set

assert os.getenv("ASTRA_DB_API_ENDPOINT") is not None, "Astra DB API endpoint is not set."

assert os.getenv("ASTRA_DB_APPLICATION_TOKEN") is not None, "Astra DB application token is not set."

assert os.getenv("KEY") is not None, " key is not set."


# Configure your embedding model and vector store

embedding = OpenEmbeddings()

vstore = AstraDBVectorStore(

    collection_name="retail",

    embedding=embedding,

    token=os.getenv("ASTRA_DB_APPLICATION_TOKEN"),

    api_endpoint=os.getenv("ASTRA_DB_API_ENDPOINT")

)
```

```
# Load a sample dataset

philo_dataset = load_dataset("sales/retail")["train"]


# Initialize the chain

prompt_template = "’’

Answer the question based only on the supplied context. If you don't know the answer, say you don't know the answer.

Context: {context}

Question: {question}

Your answer:

"""

prompt = ChatPromptTemplate.from_template(prompt_template)


model = Chat()

chain = (

    {"context": vstore.as_retriever(search_kwargs={"k": 3}), "question": RunnablePassthrough()}

    | prompt

    | model

    | StrOutputParser()

)
```

```
# User inputs their query

user_query = st.text_input("Enter your query:", "In the given context, what is the most Profit value and provide me the Date?")

if st.button("Submit"):

    result = chain.invoke(user_query)

    st.write(result)


# Optionally display some data or outputs

if st.checkbox('Show example entry from dataset'):

    st.write(philo_dataset[16])

# conda activate old_python_env

#  streamlit run streamlit_app1.py
```

PRODUCT RECOMMENDATION

```
import pandas as pd

import numpy as np

import nltk

from nltk.stem.snowball import SnowballStemmer

import streamlit as st

from sklearn.metrics.pairwise import cosine_similarity

from sklearn.feature_extraction.text import TfidfVectorizer


# Load the data

data = pd.read_csv("marketing_sample_for_amazon_com-ecommerce_20200101_20200131_10k_data.csv")


selected_products = data[['Uniq Id', 'Product Name', 'Category', 'About Product', 'Image', 'Product Url']]


def tokenize_stem(text):
    stemmer = SnowballStemmer('english')
    tokens = nltk.word_tokenize(text.lower())
    stemmed = [stemmer.stem(w) for w in tokens]
    return stemmed
```

```
selected_products['stemmed'] = selected_products.apply(lambda row: tokenize_stem(str(row['About Product']) + " " + str(row['Product Name'])), axis=1)


Tfid_Vectorize = TfidfVectorizer()


def cosine_sim(text1, text2):
    text1_con = ' '.join(text1)


    text2_con = ' '.join(text2)
    tfidf = Tfid_Vectorize.fit_transform([text1_con, text2_con])
    return cosine_similarity(tfidf[0:1], tfidf[1:2])[0][0]


def search_product(query):
    stemmed_query = tokenize_stem(query)
    selected_products['similarity'] = selected_products['stemmed'].apply(lambda x: cosine_sim(stemmed_query, x))
    res = selected_products.sort_values(by=['similarity'], ascending=False).head(10)[['Product Name', 'Category', 'About Product', 'Image', 'Product Url']]
    return res


query = st.text_input("Enter product name")
submit = st.button('Search')
```

```
if submit:
    res = search_product(query)
    recommended_product_name = []
    recommended_product_pic = []
    recommended_product_url = []

    for i in range(10):
        recommended_product_name.append(res.iloc[i]['Product Name'])
        recommended_product_pic.append(res.iloc[i]['Image'])
        recommended_product_url.append(res.iloc[i]['Product Url'])

    cols = st.columns(7)
    for i, col in enumerate(cols):
        if i < len(recommended_product_name):
            with col:
                st.text(recommended_product_name[i])
                st.image(recommended_product_pic[i])
                url = recommended_product_url[i]
                link_text = "Click here to view the product"
                st.markdown(f"[{link_text}]({url})")
```

VISUALISATION

```
import matplotlib

matplotlib.use('Agg')  # Use non-interactive backend for Flask


from flask import Flask, render_template, request

import os

import pandas as pd

import matplotlib.pyplot as plt


app = Flask(_name_)

app.config['UPLOAD_FOLDER'] = 'uploads'


os.makedirs(app.config['UPLOAD_FOLDER'], exist_ok=True)


@app.route('/')

def index():

    return render_template('index.html')


@app.route('/upload', methods=['POST'])

def upload_file():
```

```
 if 'file' not in request.files:
        return "No file part"

    file = request.files['file']
    if file.filename == '':
        return "No selected file"

    if file:
        filepath = os.path.join(app.config['UPLOAD_FOLDER'], file.filename)
        file.save(filepath)

        # Process the file and generate the graph
        try:
            plot_graph(filepath)
            return render_template('result.html', image_url='static/graph.png')
        except Exception as e:
            return f"An error occurred: {e}"

def plot_graph(filepath):
    df = pd.read_csv(filepath)
    columns = df.columns
```

```
    # Clear previous graph
    plt.clf()

    if len(columns) == 2:
        # Bar Graph
        x, y = columns
        df.plot(kind='bar', x=x, y=y, legend=False)
    else:
        # Line Graph
        df.plot(kind='line', legend=True)

    # Save the graph
    plt.xlabel('Index')
    plt.ylabel('Values')
    plt.title('Generated Graph')
    plt.savefig('static/graph.png')

if _name_ == '_main_':
    app.run(debug=True)
```

CHAPTER-6

TESTING

6.1 TEST CASES

Test Case No.	Test Case Type	Test case Description	Expected Value	Actual Value	Result
1	Query	The Retail Edge gives output for the given query	Gives appropriate output for the query	Output is appropriate to the query	PASS

Table 6.1.1: Test Case 1 (Query)

Test Case No.	Test Case Type	Test case Description	Expected Value	Actual Value	Result
2	Product Name	The Retail Edge gives top 5 recommendation for the product name given	Gives appropriate top 5 products for the given product name	Output is top 5 products of the given product name	PASS

Table 6.1.2: Test Case 2 (Best Product)

Test Case No.	Test Case Type	Test case Description	Expected Value	Actual Value	Result
3	Visualization	The Retail Edge gives output graph for the given .csv file	Gives appropriate graph for the given .csv file	Output is graph of the given .csv file	PASS

Table 6.1.2: Test Case 3 (Visualization)

CHAPTER-7

SCREENSHOTS

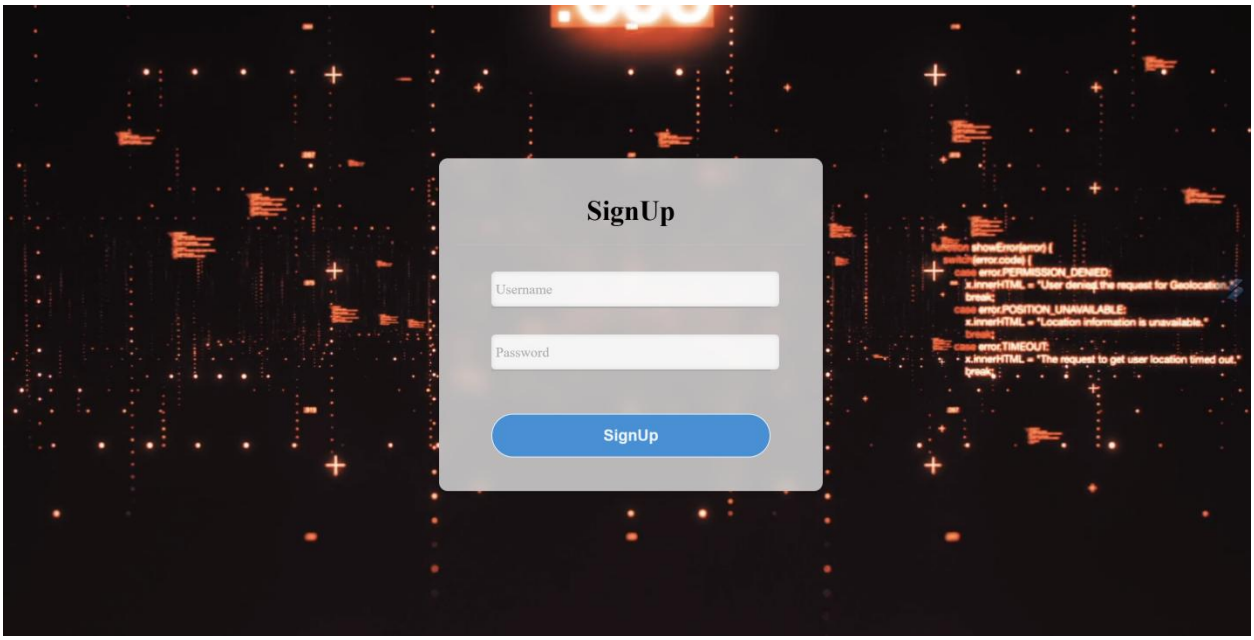

Fig.7.1: Sign Up

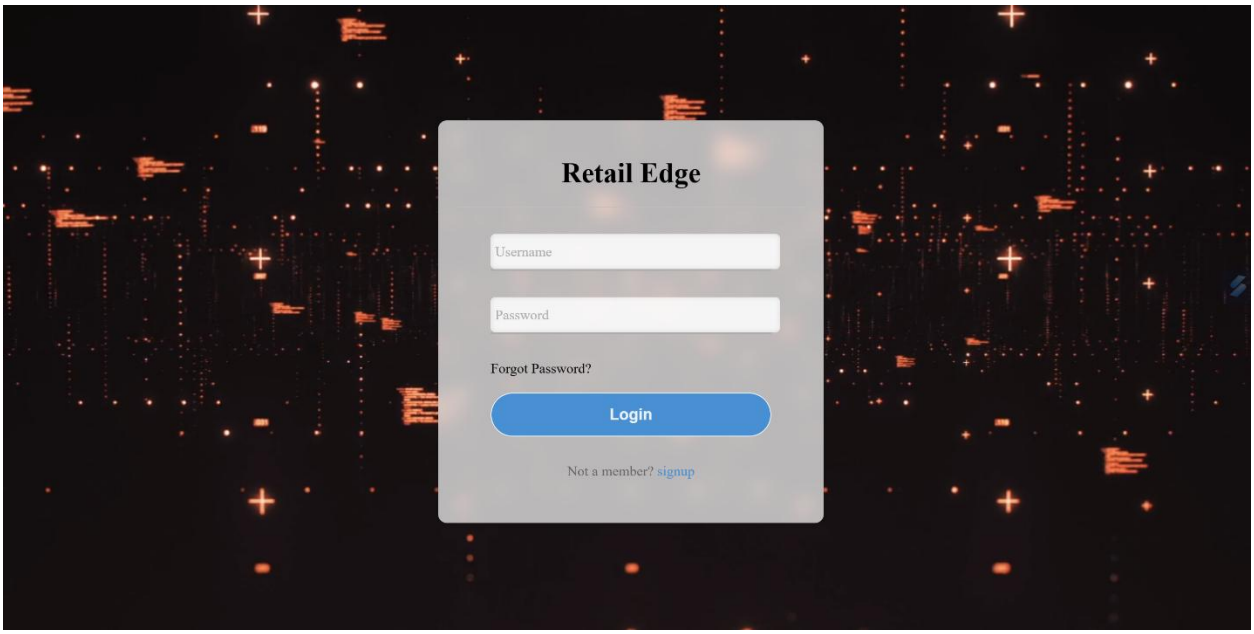

Fig.7.2: Login

Fig.7.3: Home

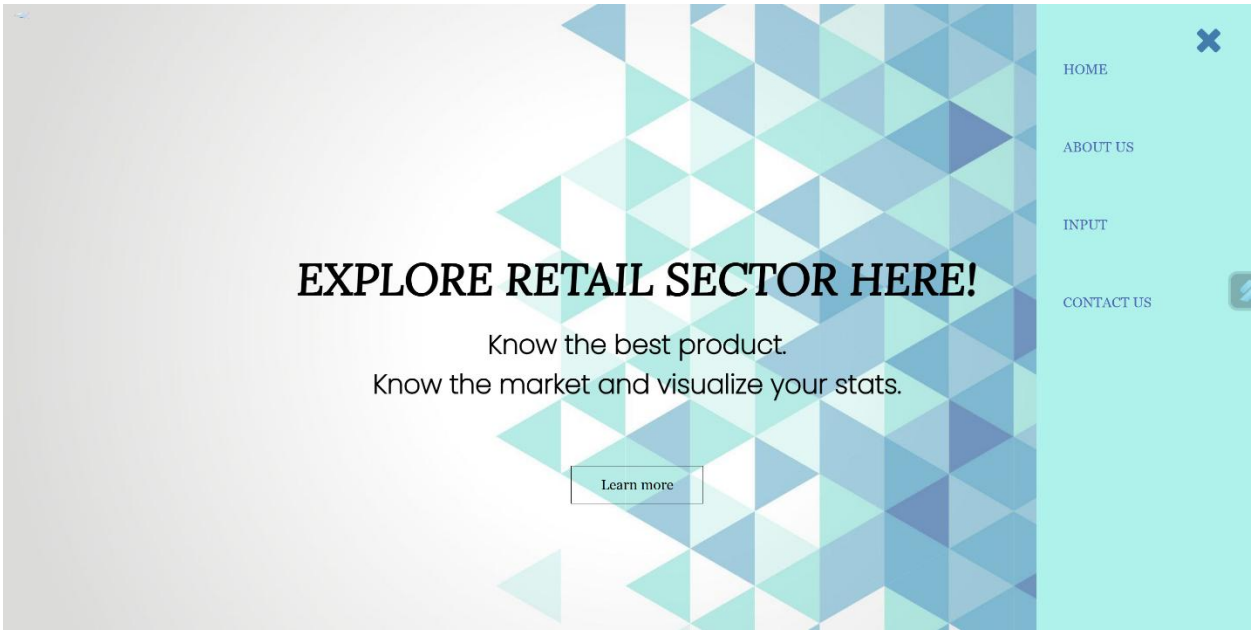

Fig.7.4: Side Bar

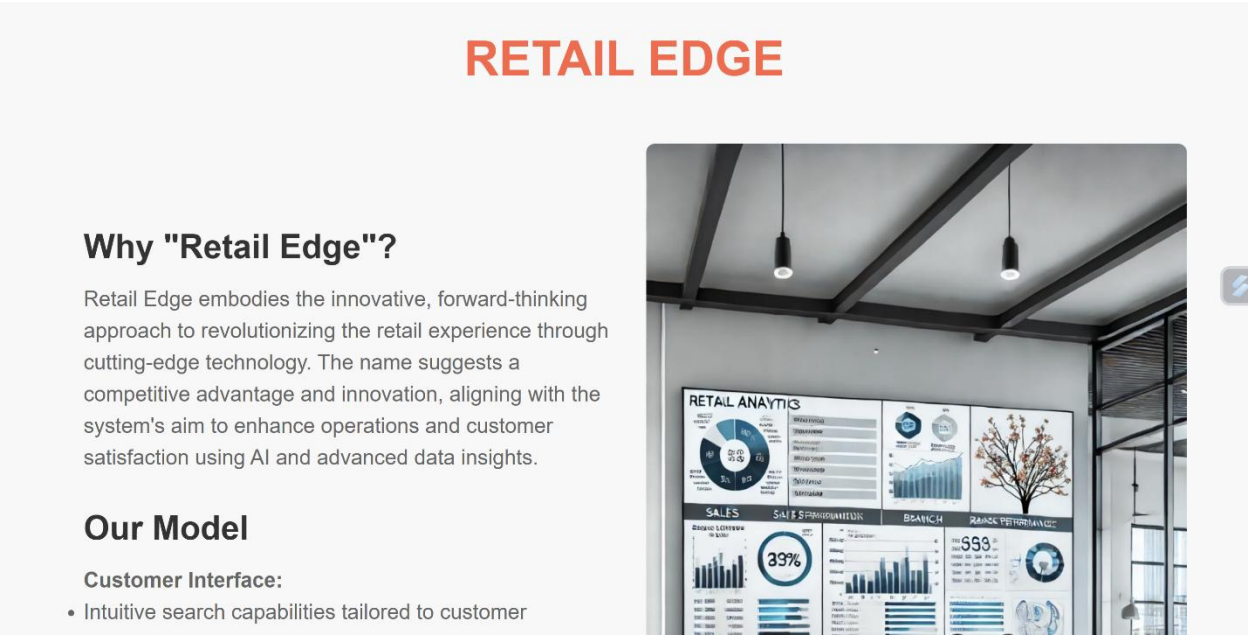

Fig.7.5: Learn More

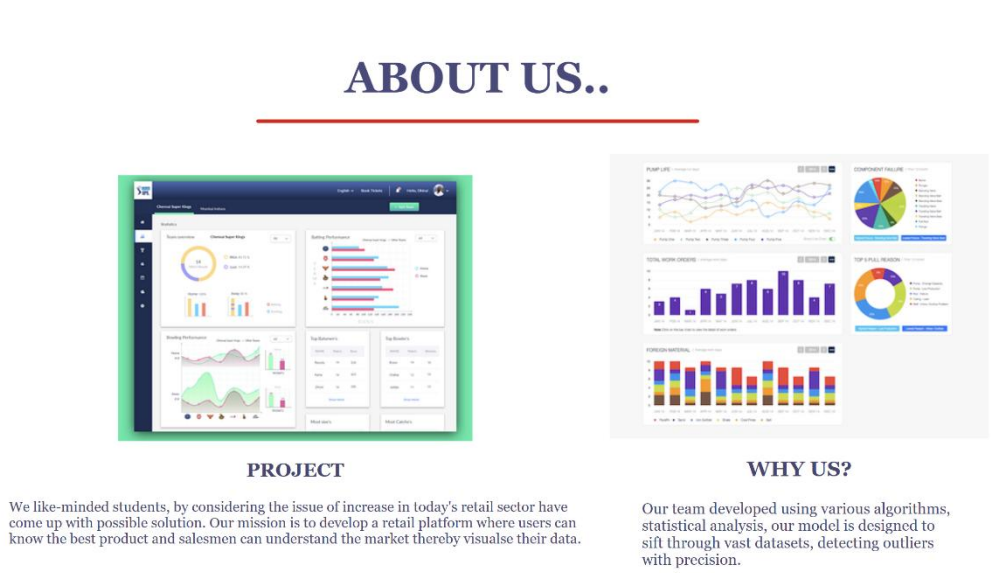

Fig.7.6: Abou Us

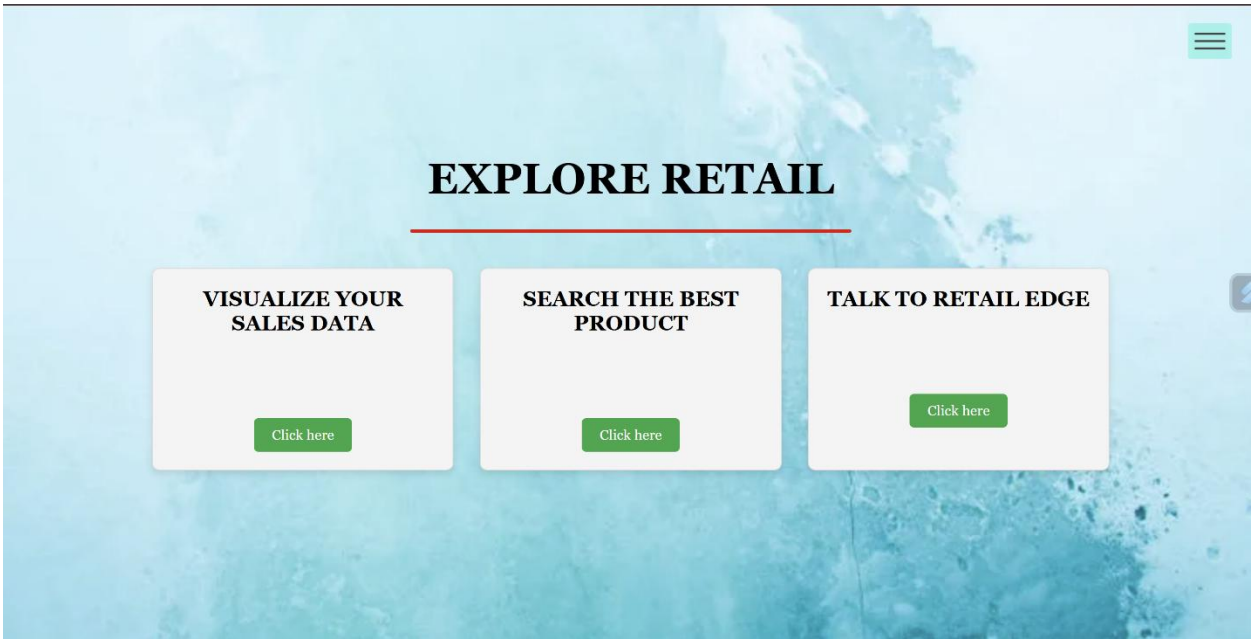

Fig.7.7: Input

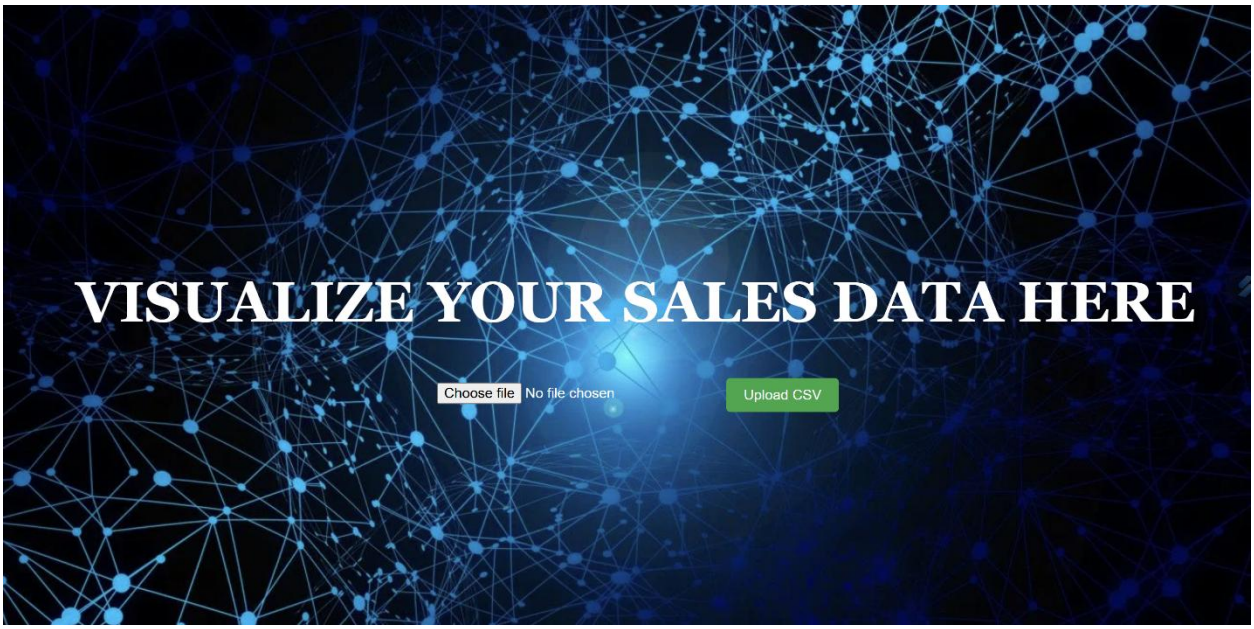

Fig.7.8: Visualize your sales data

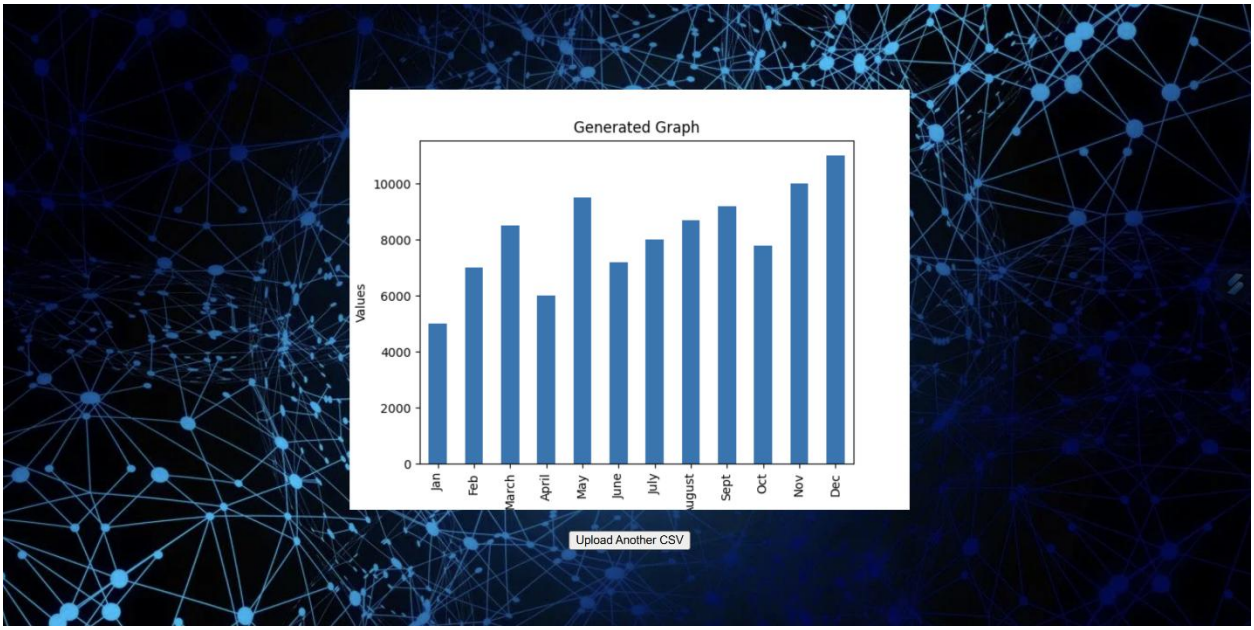

Fig.7.9: Visualization for 2 column input:

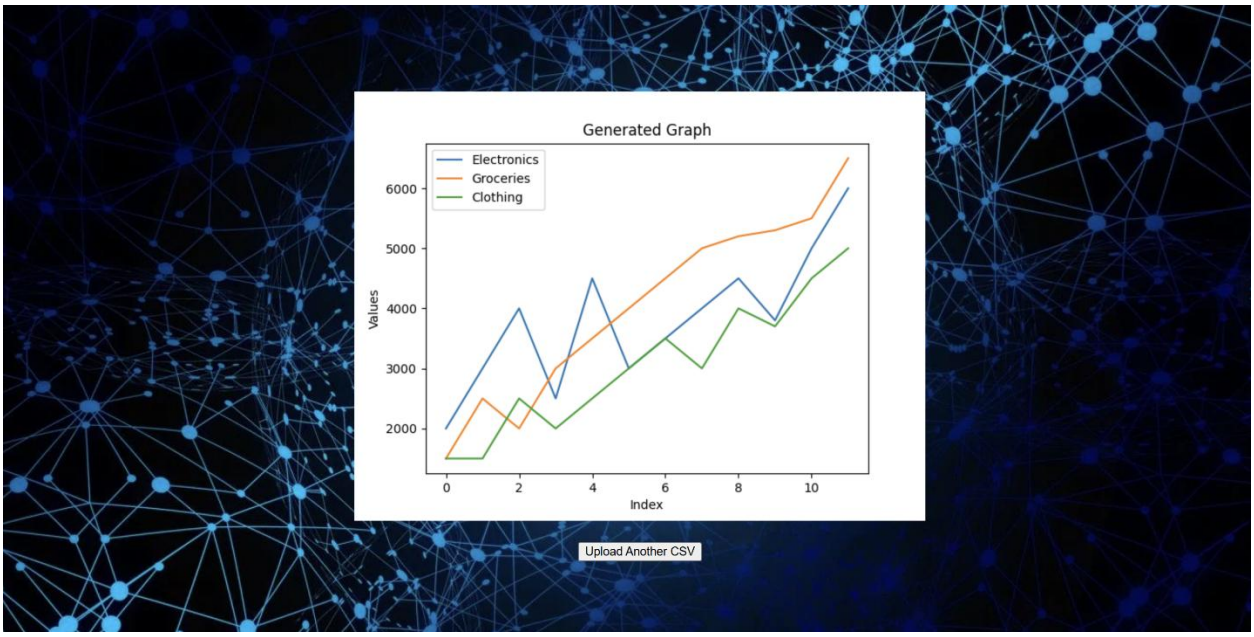

Fig.7.10: Visualization for more than 2 column input:

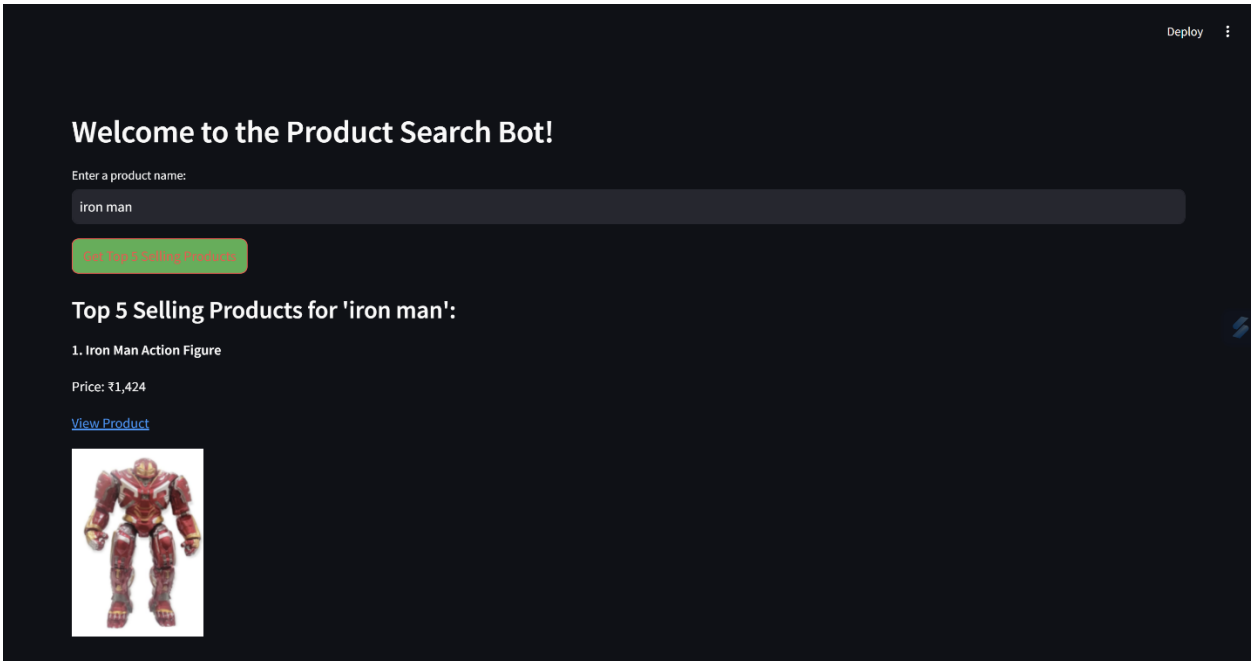

Fig.7.11: Search best product:

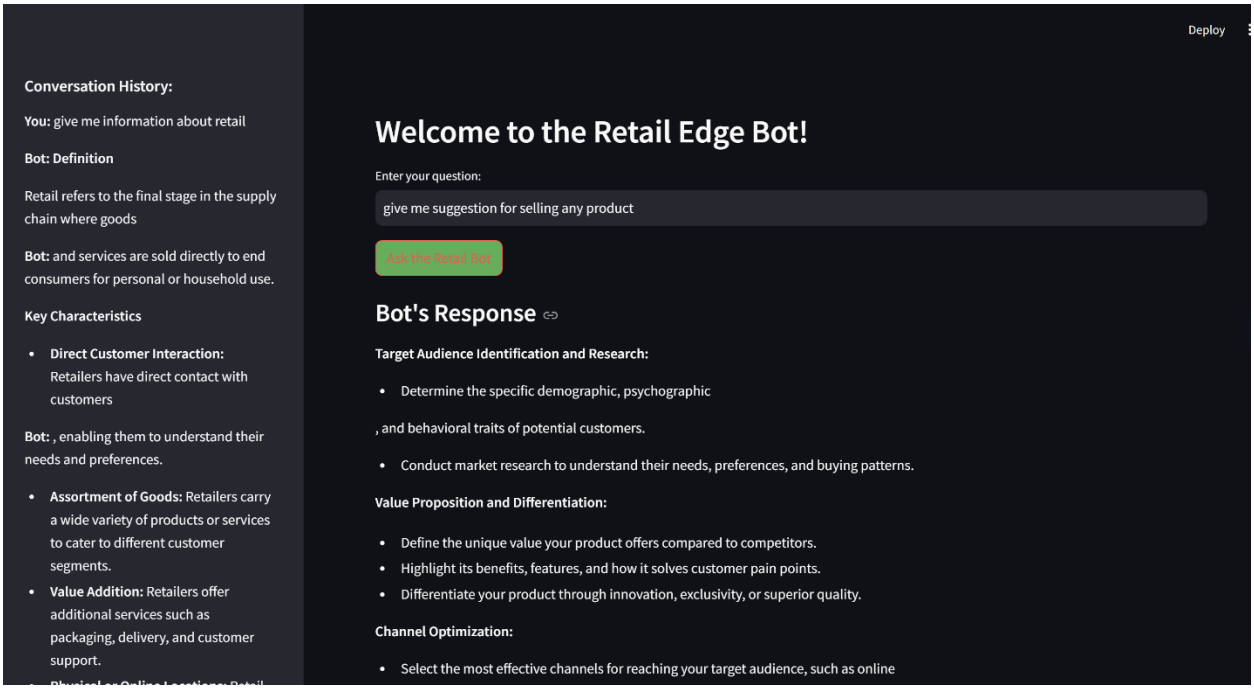

Fig.7.12: Talk to Retail Edge:

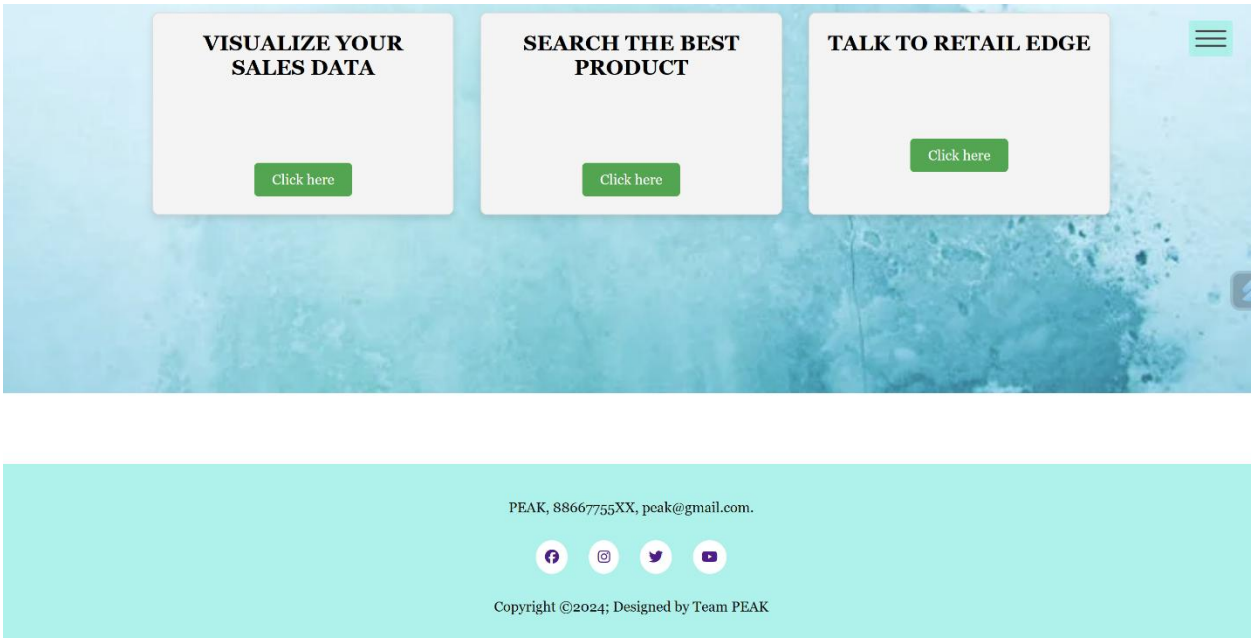

Fig.7.13: Contact Us:

CHAPTER-8

CONCLUSION AND FUTURE SCOPE

The **Retail Edge** successfully integrates advanced AI technologies like Retrieval-Augmented Generation (RAG) to address key challenges in the retail industry. By streamlining customer interactions, providing actionable insights to associates, and enabling data-driven decision-making for mart owners, the system offers a holistic solution to enhance retail efficiency and profitability.

The user-centric design, secure data handling, and scalable architecture make it a reliable and robust platform that not only improves operational workflows but also fosters customer satisfaction and business growth. This project demonstrates the potential of AI-powered solutions to redefine retail processes and drive innovation in the industry.

Future Scope:

1. **Enhanced AI Models**: Incorporate more advanced LLMs or RAG techniques for better understanding of customer queries and context.
2. **Integration with IoT Devices**: Use IoT-enabled devices to track inventory in real-time and automate stock updates.
3. **Multilingual Support**: Expand the system to support queries and interactions in multiple languages to cater to a global user base.
4. **Advanced Analytics**: Introduce predictive analytics to anticipate customer needs, forecast sales, and identify market trends.
5. **Dynamic Personalization**: Develop adaptive algorithms to provide real-time personalization based on customer preferences and behavior.

6. **Mobile Application**: Extend the platform to a mobile application for easier access and wider reach.
7. **Integration with Payment Systems**: Enable secure payment options to provide end-to-end support for retail transactions.

These enhancements will ensure the system remains at the forefront of innovation and continues to adapt to evolving retail industry needs.

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APPENDIX A: Tools and Technology

- **Frontend Development:**
    - JavaScript Frameworks: React.js
    - Python Framework: Streamlit
    - UI Components: Bootstrap
- **Backend Development:**
    - Programming Languages: Python, JavaScript (Node.js)
    - Frameworks: Express.js (Node.js)
    - Database: MongoDB, AstraDB (vector database)
- **Machine Learning and Natural Language Processing (NLP)**:
    - NLP Libraries: NLTK (Natural Language Toolkit),
    - Model: RAG Implementation
    - Visualization: Matplotlib

DESCRIPTION:

1. Programming Languages

- Python: Python serves as the backbone for developing machine learning and deep learning models in the project. It is also used for tasks such as data preprocessing, feature extraction, and implementing advanced NLP techniques to analyze review content and detect fraudulent patterns.
- JavaScript: JavaScript is employed for creating an interactive and user-friendly front-end for the web application. It enables dynamic functionalities, ensuring users can seamlessly interact with the platform.

2.Web Development Tools

- MongoDB: Stores structured and unstructured data, including user inputs, review logs, and processed data for predictions.
- Express.js: Manages server-side operations, handling API requests and data communication between the front-end and back-end.
- Node.js: Serves as the runtime environment for executing server-side logic, ensuring smooth interactions between the front-end and database.

3. Databases

- MongoDB: This NoSQL database stores user information, submitted reviews, and logs of analyzed reviews. Its flexibility allows efficient handling of both structured and unstructured data, supporting scalability as the project grows.
- Astra DB: Astra DB is a cloud-native NoSQL database built on Apache Cassandra. It efficiently manages large volumes of data with low latency and high availability. Ideal for modern applications, Astra DB supports distributed workloads and can store data like user interactions, processed outputs, and AI model configurations. Its scalability, flexible data model, and robust security features make it a reliable choice for growing, real-time applications

4.Middleware

- Node.js: Node.js acts as middleware to ensure seamless communication between the client-side and server-side components of the application. It efficiently handles asynchronous operations, enabling real-time interactions during review submissions and results display.
- Express.js: Manages server-side operations, handling API requests and data communication between the front-end and back-end.

5. Other Tools

- Git: Git is employed for version control and collaboration, enabling the team to track changes, merge updates, and maintain a stable codebase throughout the development process.
- Google Colab: Google Colab is used for prototyping and testing machine learning models in a cloud environment. It provides access to GPUs for faster computation, simplifying the iterative process of model refinement.