Customer Personality Analysis- Understanding Your Ideal Customers

Shashank Shukla

Introduction-

- Customer Personality Analysis is a detailed analysis of a company's ideal customers. It helps a business to better understand its customers and makes it easier for them to modify products according to the specific needs, behaviors, and concerns of different types of customers.

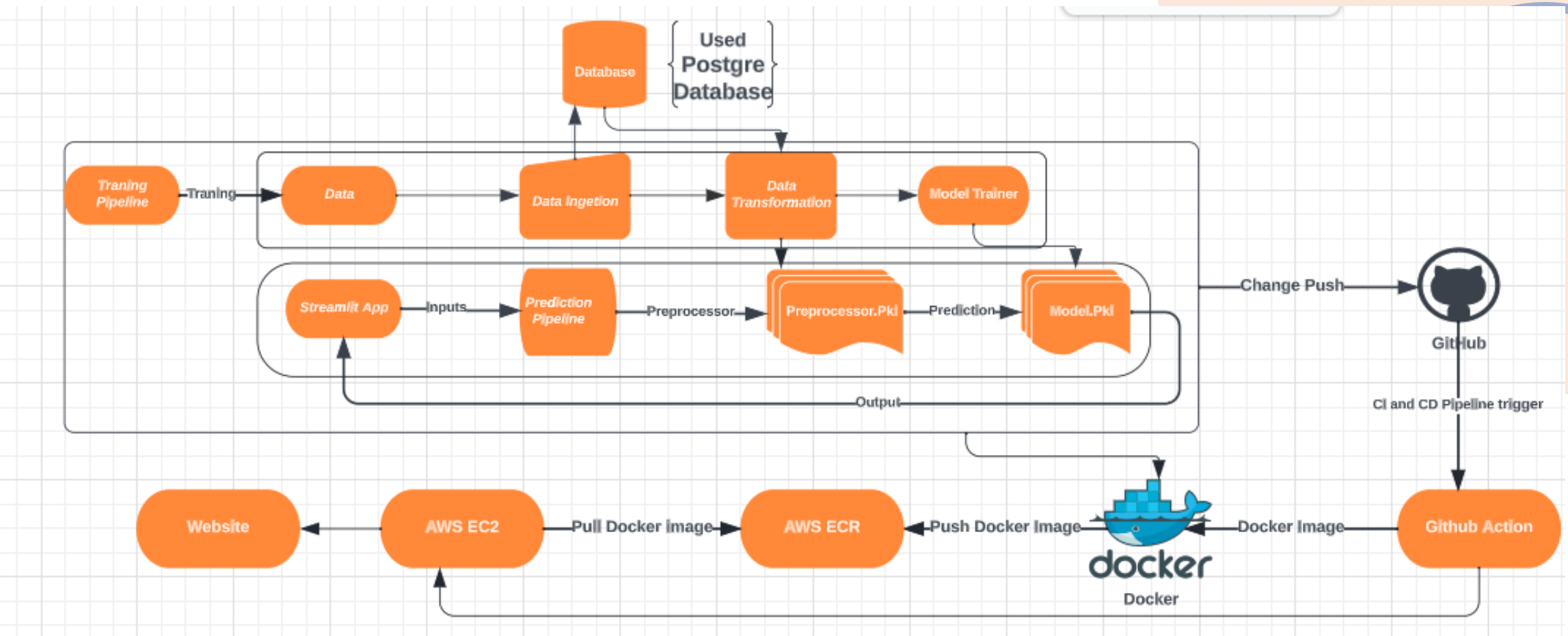
Content-

- Brief overview of Customer Personality Analysis.
- Importance of understanding ideal customers.
- Mention the problem statement.

Agenda --

Customer Sentiment Analysis- Understand customers' attitudes towards the product.
Behavior Analysis- Analyze what customers do rather than what they say about the product.

Architecture -



Data Ingestion-

DataFrame to Database: Load data into a DataFrame and use SQLAlchemy to seamlessly transfer it into a database.

Custom Ingestion Function: Create a tailored function using SQLAlchemy to handle data ingestion, schema definition, and table creation.

Scalability and Efficiency: Optimize data ingestion for scalability and performance with techniques like bulk inserts and connection pooling.

Data Transformation-

The data transformation phase is a critical step in preparing the dataset for analysis and modeling. It involves several key operations to ensure data quality, enhance features, and make it suitable for machine learning. The transformations applied include data type conversion, feature engineering, data cleaning, and encoding.

- Date Conversion-
- The 'dt_customer' column, which represents the date when a customer became a client, was converted from a string format ('%d-%m-%Y') to a datetime format for date-based calculations.

Feature Engineering-

The 'customer_for' column was created to calculate the number of months a customer has been with the company, based on the 'dt_customer' column.

The 'Age' column was computed by subtracting the birth year from the current year.

The 'Spent' column was created by summing the spending across various product categories.

The 'living_with' column was created to simplify marital status categories, mapping 'Married' and 'Together' to 'Partner' and other categories to 'Single'.

The 'children' column was calculated by summing the 'kidhome' and 'teenhome' columns to determine the total number of children in a household.

The 'Family_Size' column was introduced to represent family size, with 'Single' households assigned a size of 1 and 'Partner' households assigned a size of 2.

The 'Is_Parent' column was computed to identify whether a customer is a parent based on the presence of children.

The 'education' column was standardized to categorize education levels as 'Undergraduate', 'Graduate', or 'Postgraduate' for consistency.

Age groups were defined in the 'AgeGroup' column, categorizing customers as 'Teen', 'Adult', 'Middle Age Adult', or 'Senior Adult' based on their age.

Data Cleaning and Encoding

Data Cleaning-

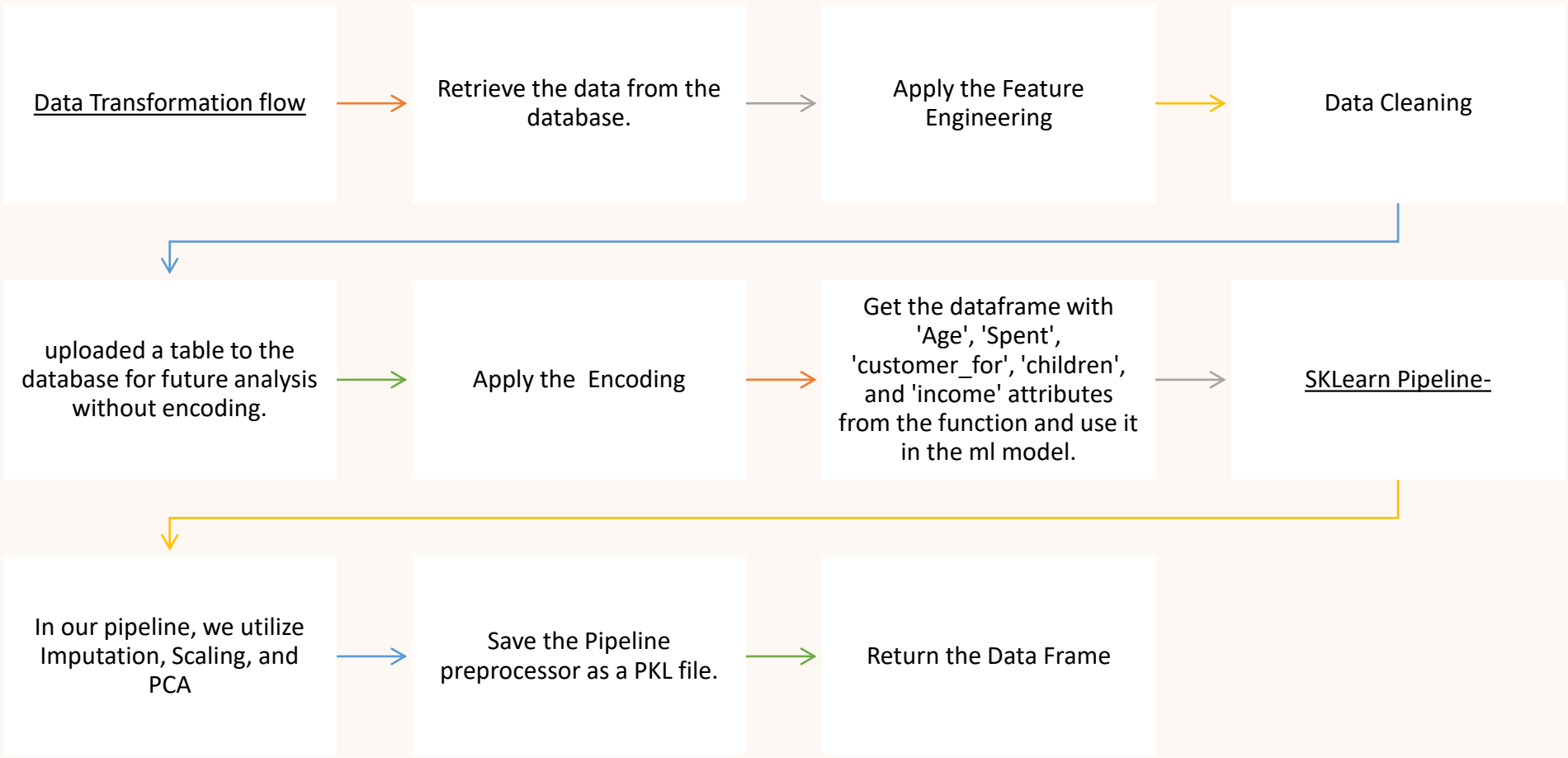
Outliers were removed from the dataset by filtering out customers with an age exceeding 100 years or an income above $120,000.

Several unnecessary columns, including 'marital_status', 'dt_customer', 'z_costcontact', 'z_revenue', 'year_birth', 'id', 'AgeGroup', and 'living_with', were dropped from the dataset as they were no longer needed for analysis or modeling.

Encoding-

Label encoding was applied to categorical columns using the LabelEncoder from the scikit-learn library. This encoding converts categorical values into numerical values for machine learning algorithms..

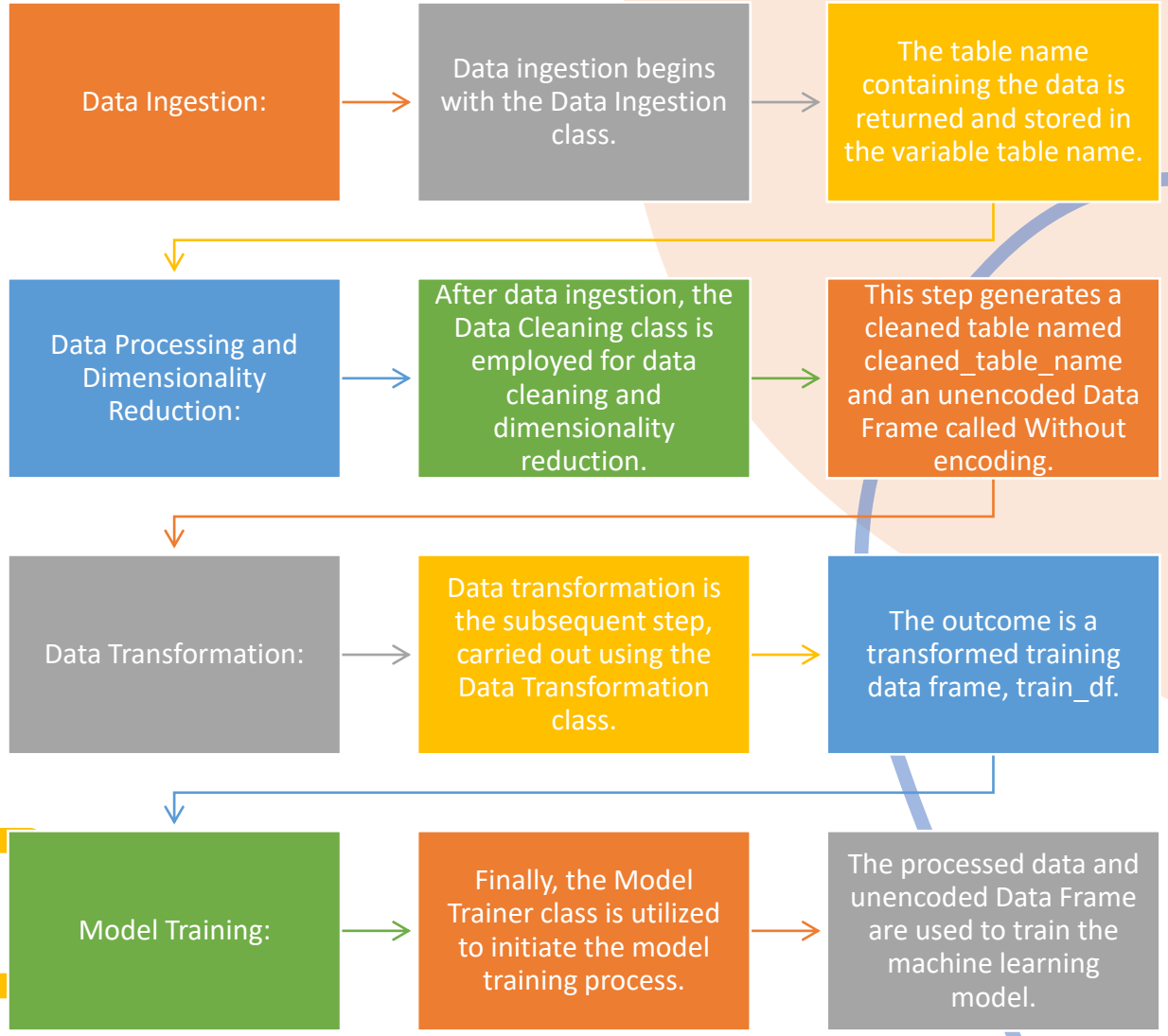
Data Transformation Flow



Model Training-

1. Utilize the Knee Python library to determine the optimal number of clusters for K-means clustering.
2. Train the K-means clustering model using the selected number of clusters.
3. Save the Model for further use as an PKL file
4. Predict cluster assignments and rename clusters based on Exploratory Data Analysis (EDA) insights, e.g., "brouns," "silver," "gold," and "platinum."
5. Retrieve data from the database.
6. Join the cluster predictions with the dataset.
7. Re-upload the updated dataset with the cluster column back into the database.

Training Pipeline-



Prediction Pipeline-

Prediction Function:

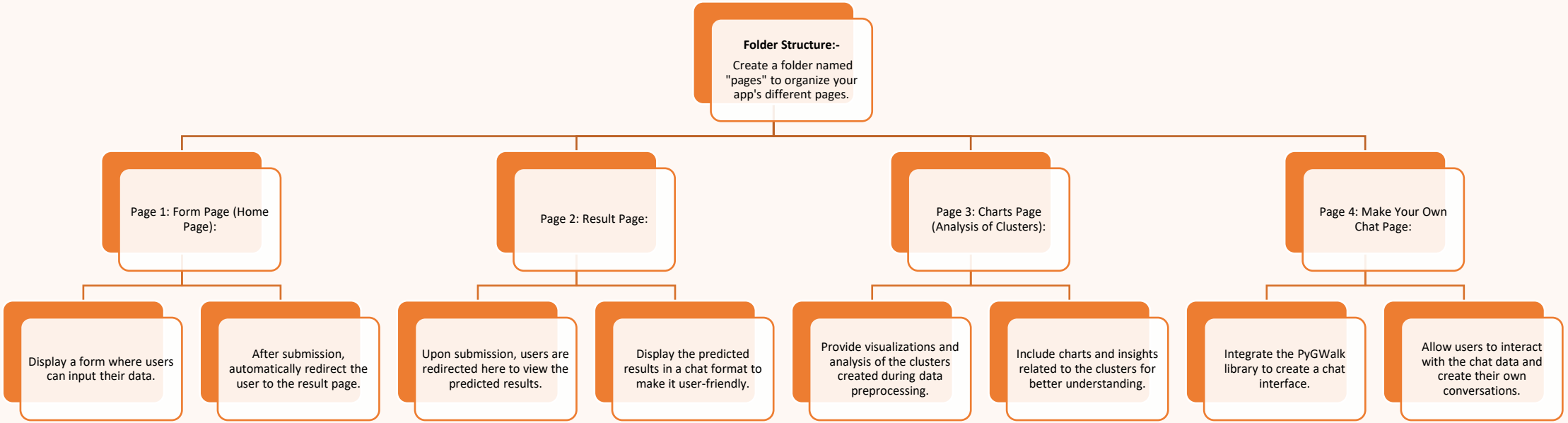
The Prediction Function is responsible for making predictions using a trained machine learning model.

It loads both the preprocessor (.pkl) file and the trained model (.pkl) file.

Input data is processed through the preprocessor to prepare it for prediction.

The model is applied to generate predictions.

Stream Lit App-



Integration of Prediction Pipeline with StreamLit-

- In the Form Page, connect the input data to the prediction pipeline.
- Upon submission, pass the input data through the prediction pipeline to generate predictions.
- Display the predicted results on the Result Page.

Streamlit App Workflow

The user visits the Home Page (Form Page) and fills in the required data.

Upon hitting the submit button, the app triggers the prediction process.

The user is redirected to the Result Page, where the predicted results are displayed in a chat format.

The user can navigate to the Charts Page to see cluster analysis and insights.

The Make Your Own Chat Page allows users to interact with existing chat data and create their own conversations.

CI/CD Pipeline-

GitHub Code Repository Update: Push your code changes to your GitHub repository, ensuring that your project is up-to-date.

GitHub Action Automation: Set up GitHub Actions to automate your CI/CD pipeline. Configure triggers to initiate workflows upon code commits and other events.

Docker Image Generation: Utilize a Dockerfile to create a Docker image encapsulating your application or service, ensuring reproducibility and portability.

AWS ECR Image Repository: Push your Docker image to Amazon Elastic Container Registry (ECR), a fully managed container registry service, ensuring secure storage and distribution.

AWS EC2 Self-hosted GitHub Runner: Activate a self-hosted GitHub runner on an Amazon EC2 instance to ensure reliable and scalable CI/CD execution. Configure it to periodically check for updates.

Pull Latest Docker Image: Enable the EC2 runner to fetch the latest Docker image from ECR, ensuring that the most current version of your application is deployed.

Execute Docker Container: Run the new Docker image on your EC2 instance, ensuring your application is up and running with the latest changes.

App Deployment-

In the deployment phase, we have established our website's hosting infrastructure using an Amazon Elastic Compute Cloud (EC2) instance. This EC2 instance functions as the platform where our website is hosted, enabling accessibility to users via the internet. This configuration provides us with the capability to deploy and operate our web application in a highly scalable and dependable manner, leveraging the robust AWS infrastructure.

thank you

Shashank Shukla

Shuklashashank297@gmail.com