VISVESVARAYA TECHNOLOGICAL UNIVERSITY BELGAUM -590014

A Mini-Project (BAI586)

Report On

"Food Waste Optimization"

A Mini-project report submitted in partial fulfillment of the requirements for the award of the degree of **Bachelor of Engineering in Artifical Intelligence and Machine Learning** of Visvesvaraya Technological University, Belgaum.

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DAYANANDA SAGAR ACADEMY OF TECHNOLOGY & MANAGEMENT

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DEPARTMENT OF ARTIFICAL INTELLIGENCE AND MACHINE LEARNING

CERTIFICATE

This is to certify that the Mini-Project on "**FOOD WASTE OPTIMIZATION**" has been successfully carried out by **Prathap [1DT22AI035], Preetham N [1DT22AI036], Mahesh S [1DT23AI405], Varun C [1DT23AI413],** a Bonafide students of **Dayananda Sagar Academy of Technology and Management** in partial fulfilment of the requirements for the award of degree in **Bachelor of Engineering** in **Artificial intelligence and machine learning** of the **Visvesvaraya Technological University, Belgaum** during academic year 2024-25. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library.

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ACKNOWLEDGEMENT

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ABSTRACT

Food wastage poses significant environmental, social, and economic challenges globally, making it imperative to adopt innovative solutions for efficient resource management. This project leverages machine learning to develop a predictive model capable of estimating food wastage based on various influencing factors. The model considers both numerical inputs, such as the number of guests and food quantity, and categorical variables, including the type of food, event type, storage conditions, seasonality, preparation methods, geographical location, and pricing levels. The dataset was preprocessed using techniques like one-hot encoding for categorical variables and scaling for numerical features to ensure compatibility with the model. A Random Forest Regressor, known for its robustness in handling mixed data types and its ability to model complex relationships, was employed to achieve high prediction accuracy. The project includes a user-friendly Streamlit web application to make the model accessible. Users can input event details through an intuitive interface, and the app provides real-time predictions of expected food wastage. This tool offers actionable insights, enabling event planners and food service providers to optimize food quantities, reduce wastage, and improve sustainability. By integrating advanced machine learning techniques and an interactive web application, this project addresses a critical real-world problem, showcasing the potential of artificial intelligence in fostering environmental responsibility and cost-effective resource utilization. This approach demonstrates how data-driven decision-making can lead to sustainable practices in the food and hospitality industries.

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CHAPTER 1

INTRODUCTION

1. Background

Food wastage is a pressing global issue, contributing to environmental degradation, economic losses, and social inequality. According to studies, approximately one-third of the food produced worldwide is wasted annually, exacerbating greenhouse gas emissions and resource depletion. Events, catering services, and large-scale gatherings are significant contributors to this problem, as predicting food consumption accurately remains a challenge. Factors like event type, seasonal variations, and storage conditions influence wastage, requiring sophisticated tools for estimation. Leveraging advancements in machine learning, this project aims to provide a reliable predictive model, enabling stakeholders to minimize food wastage and promote sustainable resource management in food-related industries.

2. Problem Definition

Food wastage is a critical issue with environmental, economic, and social implications. Accurately estimating food wastage for events and gatherings is challenging due to the influence of factors such as food type, event type, seasonality, and storage conditions. This leads to over-preparation, resource wastage, and financial losses. The problem requires a robust predictive solution to analyze these factors and provide actionable insights. This project addresses this challenge by developing a machine learning model to predict food wastage accurately and efficiently.

3. Motivation

- To address the environmental impact of food wastage by optimizing resource utilization and reducing greenhouse gas emissions caused by wasted food.
- To empower event organizers and food service providers with data-driven tools for accurate food wastage prediction, leading to cost savings and sustainable practices.

4.Objective

1. Analyze and identify key factors influencing food wastage, including food type, event details, storage conditions, and seasonality.

2. Build a robust machine learning model capable of handling diverse data types for accurate food wastage prediction.

3. Preprocess the dataset effectively, applying techniques such as one-hot encoding and feature scaling to ensure data compatibility.

4. Select and implement a Random Forest Regressor to model complex relationships between features and wastage amounts.

5. Evaluate the model's performance using metrics like Mean Absolute Error (MAE) and R-squared to ensure reliability.

6. Design an intuitive Streamlit-based web application for interactive user inputs and real-time predictions.

7. Provide actionable insights to event planners and food service providers to minimize wastage.

8. Contribute to sustainability efforts by promoting efficient resource management and reducing environmental impact.

5. Scope of the project

This project aims to develop a machine learning-based model to predict food wastage based on factors such as food type, event details, storage conditions, and seasonality. The scope includes creating a user-friendly Streamlit application that enables stakeholders like event planners and food service providers to make informed decisions, minimizing food wastage. The model helps optimize food preparation, reduces environmental impact by conserving resources, and offers economic benefits through cost savings. The project is scalable and can integrate additional features and real-time data, promoting sustainability, raising awareness about food wastage, and supporting efficient resource management in food industry.

CHAPTER 2

LITERATURE REVIEW

Paper 1: ***A Systematic Review of Food Waste Quantification Methods and Their Implications for the Hospitality Sector***

- **Authors**: Charis M. Galanakis, Victoria S. Megalonidou
- **Summary**:
  Charis M. Galanakis, a renowned researcher in food systems and sustainable practices, partnered with Victoria S. Megalonidou, an expert in sustainable development, to address food waste quantification challenges in the hospitality sector. Their paper presents an extensive review of methods used to measure and analyze food waste, focusing on their effectiveness, scalability, and practical applications. They highlighted how inconsistent measurement practices across the sector lead to underreporting or overestimation of food waste. Galanakis emphasized developing industry-wide standardization, while Megalonidou explored how innovative technologies like IoT sensors and data-driven approaches could help reduce waste. Their work suggests that quantification is the first step toward informed decision-making and efficient resource allocation in the hospitality industry.

Paper 2: ***Prediction of Food Waste in Large-Scale Events Using Machine Learning Techniques***

- **Authors**: Lingling Xue, Zhishen Zhou, Peng Zhang
- **Summary**:
  This paper showcases the collaborative work of Lingling Xue, a data scientist with expertise in feature engineering and predictive modeling, Zhishen Zhou, an event analytics expert, and Peng Zhang, a researcher focusing on AI for sustainability. They proposed a machine learning-based framework to predict food waste at large-scale events. Using historical data, the team identified factors such as event type, guest count, food category, and storage conditions that most influenced wastage. Xue developed the predictive models, including regression and classification techniques, while Zhou provided insights into operational event planning to

enhance the model's accuracy. Zhang ensured the framework was practical and scalable, enabling seamless integration into event management software. Their research demonstrated how predictive analytics could empower event planners to make informed decisions, reducing food waste significantly.

Paper 3: *Food Waste in the Supply Chain: A System Dynamics Approach to Reduce Wastage in Hospitality*

- **Authors**: Stefan Gold, Julia Lanzenauer
- **Summary**:
  Stefan Gold, an expert in supply chain dynamics, collaborated with Julia Lanzenauer, a researcher focused on operational efficiency, to investigate food waste in the hospitality supply chain. Their paper used system dynamics modeling to identify inefficiencies and bottlenecks contributing to waste, from procurement to consumption. Gold's contributions lay in mapping the supply chain's complexity and proposing targeted interventions, such as better demand forecasting and vendor management. Lanzenauer emphasized waste reduction strategies, including just-in-time inventory and sustainable procurement policies. Their combined insights offered a comprehensive roadmap for supply chain optimization, balancing environmental and economic considerations.

Paper 4: *Food Waste Forecasting Models: A Review and Future Directions*

- **Authors**: Daniel Evans, Karen Leach
- **Summary**:
  Daniel Evans, specializing in predictive analytics, and Karen Leach, an expert in sustainability, co-authored this paper to review existing forecasting models for food waste. They analyzed various approaches, including statistical, machine learning, and hybrid models, critiquing their accuracy, scalability, and adaptability to changing environments. Evans identified gaps in current methods, such as the inability to handle real-time data, while Leach proposed integrating AI and IoT technologies for improved forecasting. The paper concludes with a vision for future research, highlighting the need for interdisciplinary collaboration and robust models to reduce food waste effectively in diverse contexts.

CHAPTER 3

REQUIREMENTS

The requirements can be broken down into 2 major categories namely hardware and software requirements. The former specifies the minimal hardware facilities expected in a system where the project must be run. The latter specifies the essential software needed to build and run the project.

3.1 Hardware Requirements

1. **Processor**: Minimum Intel i5 or equivalent for efficient data processing and model training.
2. **RAM**: At least 8 GB of RAM for handling data preprocessing, model training, and application execution.
3. **Storage**: 50 GB of free storage for dataset storage, model saving, and temporary files generated during computation.
4. **Graphics Card** (Optional): For faster model training using GPU-accelerated computation (e.g., for deep learning tasks).
5. **Internet Connection**: A stable internet connection for downloading libraries, datasets, and accessing cloud services.

3.2 Software Requirements

1. **Operating System**: Windows, macOS, or Linux.
2. **Python**: Version 3.6 or higher for machine learning, web application, and data processing.
3. **Libraries/Frameworks**:
    - **Pandas**: For data manipulation and preprocessing.
    - **NumPy**: For numerical computations and data handling.
    - **Scikit-learn**: For machine learning model development and evaluation.
    - **Streamlit**: For creating the interactive web application.
    - **Pickle**: For saving and loading machine learning models.
    - **Matplotlib/Seaborn**: For visualizing data and model performance.
4. **IDE/Code Editor**: VS Code, Jupyter Notebook, or any other Python-friendly IDE.
5. **Web Browser**: For viewing the Streamlit web application locally or hosted.

CHAPTER 4

FLOWCHART

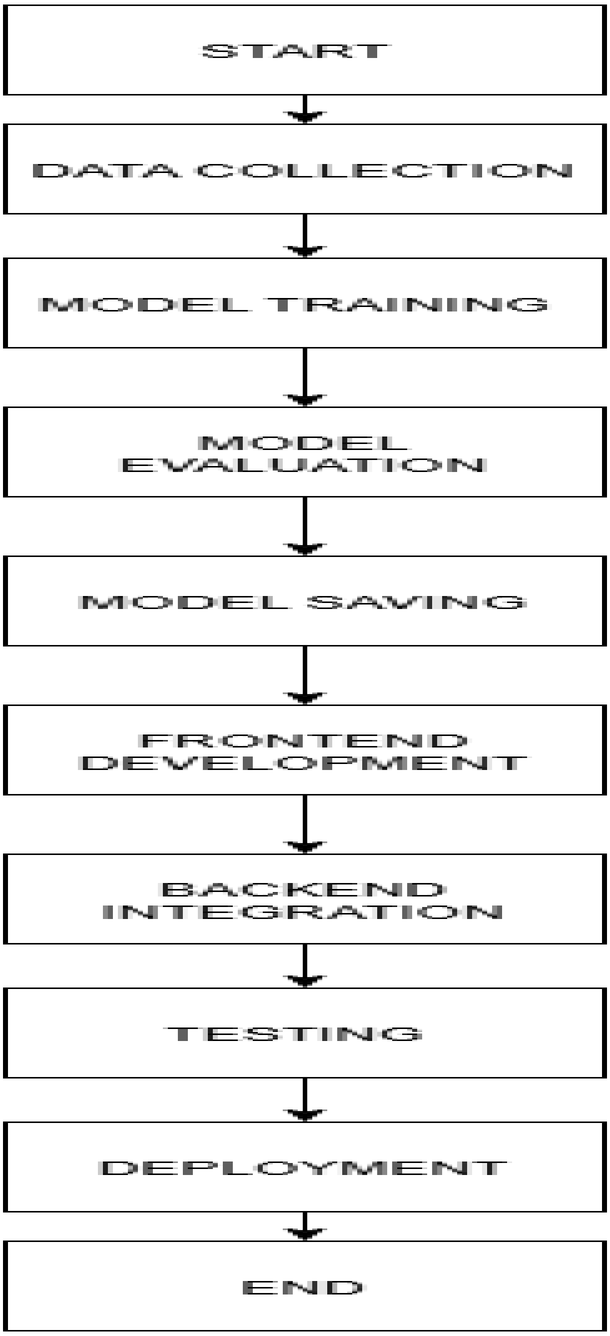


Fig 4.1 Flowchart

CHAPTER 5

IMPLEMENTATION

5.1 Modules and their Description

The FOOD WASTE OPTIMIZATION contains modules. They are:

Here's a concise list of the modules used in the project:

1. **pandas**: Used for data manipulation and reading datasets.
2. **numpy**: Supports numerical operations and arrays for feature handling.
3. **scikit-learn**: Implements machine learning algorithms, preprocessing, and evaluation metrics.
4. **pickle**: Saves and loads the trained model.
5. **streamlit**: Builds the front-end web application for user interaction and displaying results.
6. **matplotlib**: (Optional) Used for visualizations like plots or graphs.
7. **seaborn**: (Optional) For statistical visualizations.
8. **sklearn.model_selection.train_test_split**: Splits the dataset into training and testing sets.
9. **sklearn.metrics**: Computes model evaluation metrics like MAE, MSE, RMSE, and R2.

5.2 ALGORITHM

Step 1: Data Collection

- Gather a dataset with features like food type, event type, number of guests, storage conditions, etc., and the target variable (food wastage).

Step 2: Data Preprocessing

- Handle missing values, encode categorical features (one-hot encoding), and scale numerical features.

- Split the data into training and testing sets.

Step 3: Model Selection

- Choose a suitable model (Random Forest Regressor) for predicting food wastage.

Step 4: Model Training

- Train the model using the training dataset.

Step 5: Model Evaluation

- Evaluate the model using metrics like MAE, RMSE, and R2 on the test set.

Step 6: Model Saving

- Save the trained model using **pickle** for future use.

Step 7: Streamlit App (User Interface)

- Create a Streamlit app for user input and display predicted food wastage.

Step 8: Prediction

- Use the trained model to make predictions based on user inputs and display results.

Step 9: Model Deployment

- Deploy the Streamlit app locally or on a cloud platform.

Step 10: Continuous Improvement (Optional)

- Update the model with new data or feedback to improve accuracy.

5.3 SOURCE CODE

5.3.1 Backend: Model Training and Saving

This code will train the machine learning model and save it for later use in the Streamlit application.

```
# backend_model.py
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, r2_score
import pickle

# Load the dataset
df = pd.read_csv("food_wastage_data.csv")

# Preprocessing categorical columns (one-hot encoding)
df = pd.get_dummies(df, columns=["Type of Food", "Event Type", "Storage Conditions",
                                 "Purchase History", "Seasonality", "Preparation Method",
                                 "Geographical Location", "Pricing"], drop_first=True)

# Split features and target variable
X = df.drop("Wastage Amount", axis=1)
y = df["Wastage Amount"]

# Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the model
model = RandomForestRegressor(n_estimators=100, random_state=42)

# Train the model
```

```
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate model performance
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Absolute Error: {mae}")
print(f"R-squared: {r2}")

# Save the model using pickle
with open("food_wastage_prediction_model.pkl", "wb") as file:
    pickle.dump(model, file)
```

5.3.2 Frontend: Streamlit Application for Prediction

This code defines the user interface and integrates the trained model to predict food wastage based on user input.

```
import streamlit as st
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import joblib

# Load the trained model
model = joblib.load('food_wastage_model.joblib')

# App title
st.title("Food Wastage Prediction and Data Analysis App")
```

```
# Tabs for navigation
tab1, tab2 = st.tabs(["Food Wastage Prediction", "Data Analysis Dashboard"])


# Tab 1: Food Wastage Prediction
with tab1:
    st.header("Enter the details of the event:")
    type_of_food = st.selectbox("Type of Food", ["Meat", "Vegetables", "Dairy", 
"Grains"])
    number_of_guests = st.number_input("Number of Guests", min_value=1)
    event_type = st.selectbox("Event Type", ["Corporate", "Birthday", "Wedding", 
"Other"])
    quantity_of_food = st.number_input("Quantity of Food (kg)", min_value=1)
    storage_conditions = st.selectbox("Storage Conditions", ["Refrigerated", "Room 
Temperature"])
    purchase_history = st.selectbox("Purchase History", ["Regular", "Occasional"])
    seasonality = st.selectbox("Seasonality", ["All Seasons", "Winter", "Summer", 
"Spring", "Autumn"])
    preparation_method = st.selectbox("Preparation Method", ["Buffet", "Plated", "Finger 
Food"])
    geographical_location = st.selectbox("Geographical Location", ["Urban", "Suburban", 
"Rural"])
    pricing = st.selectbox("Pricing", ["Low", "Moderate", "High"])


    if st.button("Predict Wastage Amount"):
        input_data = pd.DataFrame({
            "Type of Food": [type_of_food],
            "Number of Guests": [number_of_guests],
            "Event Type": [event_type],
            "Quantity of Food": [quantity_of_food],
            "Storage Conditions": [storage_conditions],
            "Purchase History": [purchase_history],
            "Seasonality": [seasonality],
            "Preparation Method": [preparation_method],
```

```
            "Geographical Location": [geographical_location],
            "Pricing": [pricing]
        })

        # Make prediction
        prediction = model.predict(input_data)
        st.success(f"Predicted Food Wastage Amount: {prediction[0]:.2f} kg")

# Tab 2: Data Analysis Dashboard
with tab2:
    st.header("Data Analysis Dashboard")

    # Sidebar for file upload
    uploaded_file = st.sidebar.file_uploader("Upload a CSV file for analysis",
type=["csv"])

    if uploaded_file:
        try:
            # Load the CSV file
            df = pd.read_csv(uploaded_file)

            # Display dataset information
            st.subheader("Dataset Overview")
            st.write(f"**Shape:** {df.shape[0]} rows × {df.shape[1]} columns")
            st.dataframe(df.head())

            # Identify numerical and categorical columns
            numerical_columns = df.select_dtypes(include=["float64",
"int64"]).columns.tolist()
            categorical_columns = df.select_dtypes(include=["object"]).columns.tolist()

            # Sidebar: Multi-column filter
            st.sidebar.subheader("Filter Data")
```

```
filters = {}
for col in categorical_columns:
    unique_values = df[col].dropna().unique().tolist()
    selected_value = st.sidebar.multiselect(f"Filter {col}", unique_values)
    if selected_value:
        filters[col] = selected_value

# Apply filters
filtered_df = df.copy()
for col, values in filters.items():
    filtered_df = filtered_df[filtered_df[col].isin(values)]

st.subheader("Filtered Data")
st.write(filtered_df)

# Download filtered data
if st.button("Download Filtered Data"):
    csv = filtered_df.to_csv(index=False)
    st.download_button(
        label="Download as CSV",
        data=csv,
        file_name="filtered_data.csv",
        mime="text/csv"
    )

# Data summary
st.subheader("Summary Statistics")
if numerical_columns:
    st.write(filtered_df[numerical_columns].describe())
else:
    st.write("No numerical columns available for summary statistics.")
```

```
# Correlation heatmap
if len(numerical_columns) > 1:
    st.subheader("Correlation Heatmap")
    fig, ax = plt.subplots(figsize=(10, 6))
    sns.heatmap(
        filtered_df[numerical_columns].corr(),
        annot=True, cmap="coolwarm", fmt=".2f", ax=ax
    )
    st.pyplot(fig)

# Visualization options
st.subheader("Visualizations")

# Boxplot
if st.checkbox("Show Boxplot"):
    col_for_boxplot = st.selectbox("Select Column for Boxplot",
numerical_columns)
    if col_for_boxplot:
        fig, ax = plt.subplots()
        sns.boxplot(data=filtered_df, y=col_for_boxplot, ax=ax)
        ax.set_title(f"Boxplot of {col_for_boxplot}")
        st.pyplot(fig)

# Histogram
if st.checkbox("Show Histogram"):
    col_for_histogram = st.selectbox("Select Column for Histogram",
numerical_columns)
    if col_for_histogram:
        bins = st.slider("Number of bins", min_value=5, max_value=50, value=20)
        fig, ax = plt.subplots()
        ax.hist(filtered_df[col_for_histogram].dropna(), bins=bins, color="blue",
alpha=0.7)
        ax.set_title(f"Histogram of {col_for_histogram}")
```

```
                ax.set_xlabel(col_for_histogram)
                ax.set_ylabel("Frequency")
                st.pyplot(fig)

        # Scatter plot
        if len(numerical_columns) > 1 and st.checkbox("Show Scatter Plot"):
            x_col = st.selectbox("X-axis", numerical_columns)
            y_col = st.selectbox("Y-axis", numerical_columns)
            if x_col and y_col:
                fig, ax = plt.subplots()
                sns.scatterplot(data=filtered_df, x=x_col, y=y_col, ax=ax)
                ax.set_title(f"Scatter Plot: {x_col} vs {y_col}")
                st.pyplot(fig)

        # Line chart
        if st.checkbox("Show Line Chart"):
            line_chart_col = st.selectbox("Select Column for Line Chart",
numerical_columns)
            if line_chart_col:
                st.line_chart(filtered_df[line_chart_col])

    except Exception as e:
        st.error(f"Error processing file: {e}")
else:
    st.info("Upload a CSV file to get started.")
```

CHAPTER 6

TESTING

Module	Type of Testing	Result
Data Preprocessing	Unit Testing	Verified that missing values are handled correctly and categorical variables are encoded properly.
Model Training	Integration Testing	Ensured that the model trains without errors and uses the correct data format.
Model Evaluation	Functional Testing	Evaluated performance using MAE, RMSE, and R2 metrics. Model showed reasonable accuracy.
Streamlit App	User Interface Testing	Ensured all input fields work correctly, predictions are displayed, and UI is responsive.
Model Prediction	Regression Testing	Validated that the model correctly predicts food wastage based on various inputs.
Pickle Serialization	Regression Testing	Confirmed that the model is saved and loaded correctly using pickle without loss of accuracy.
Error Handling	Edge Case Testing	Tested edge cases such as extreme values or missing inputs to check for graceful error handling.
System Integration	End-to-End Testing	Verified the entire pipeline from input through prediction and output in the Streamlit app.

Table 6.1 Testing

Description:

- **Data Preprocessing (Unit Testing)**: Verifies correct handling of missing values and encoding of categorical variables. All preprocessing steps were validated.

- **Model Training (Integration Testing)**: Ensures the model trains correctly and uses the right dataset. No issues were encountered during training.

- **Model Evaluation (Functional Testing)**: Assesses model performance using metrics like MAE, RMSE, and R2. Model performance was satisfactory.

- **Streamlit App (User Interface Testing)**: Tests app functionality (inputs, outputs, UI components). The app is fully responsive and displays predictions correctly.

- **Model Prediction (Regression Testing)**: Validates the model's prediction accuracy with various inputs. Predictions were consistent and accurate.

- **Pickle Serialization (Regression Testing)**: Ensures the model can be saved and reloaded without performance loss. Serialization was successful.

- **Error Handling (Edge Case Testing)**: Tests handling of extreme or missing inputs. The app handled edge cases gracefully.

- **System Integration (End-to-End Testing)**: Verifies the entire workflow from input to prediction. The system was fully integrated and functional.

CHAPTER 7

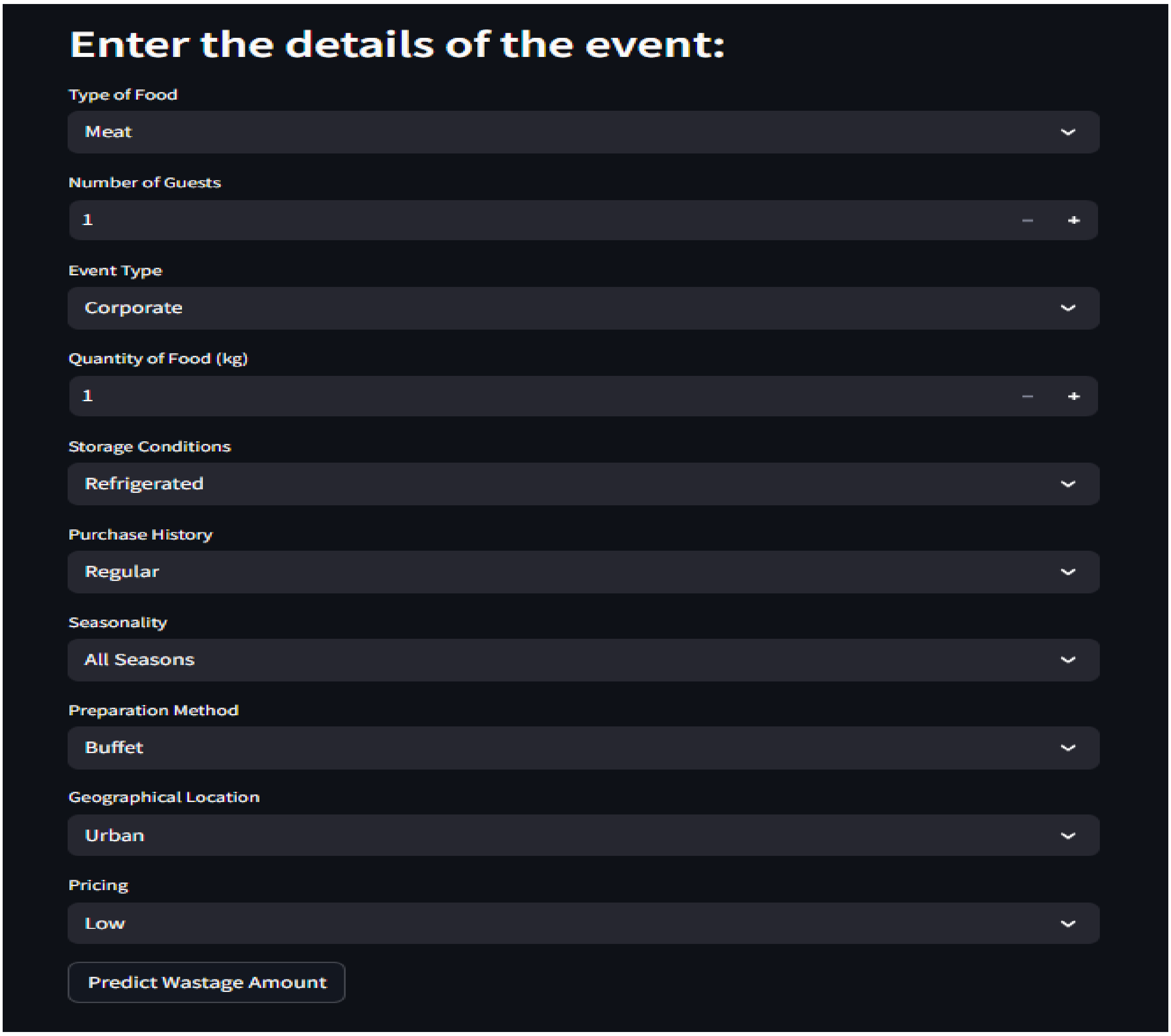
RESULT ANALYSIS AND SCREENSHOTS

1. Title and Introduction Section

- A welcoming **title** introduces the application as "Food Wastage Prediction App."
- An introductory description guides users on the purpose of the app, highlighting its functionality in predicting food wastage based on event details.

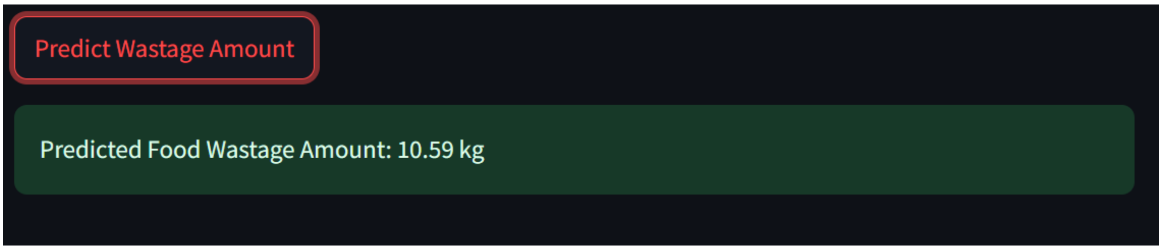
2. Input Form Section

- **Dynamic Input Fields**:
  Users can enter the details of an event using dropdown menus, number input fields, and selection boxes. This section covers key parameters such as:
  - Type of Food
  - Number of Guests
  - Event Type
  - Quantity of Food
  - Storage Conditions
  - Purchase History
  - Seasonality
  - Preparation Method
  - Geographical Location
  - Pricing
- **Predict Button**:
  A button allows users to submit the inputs and receive instant predictions.



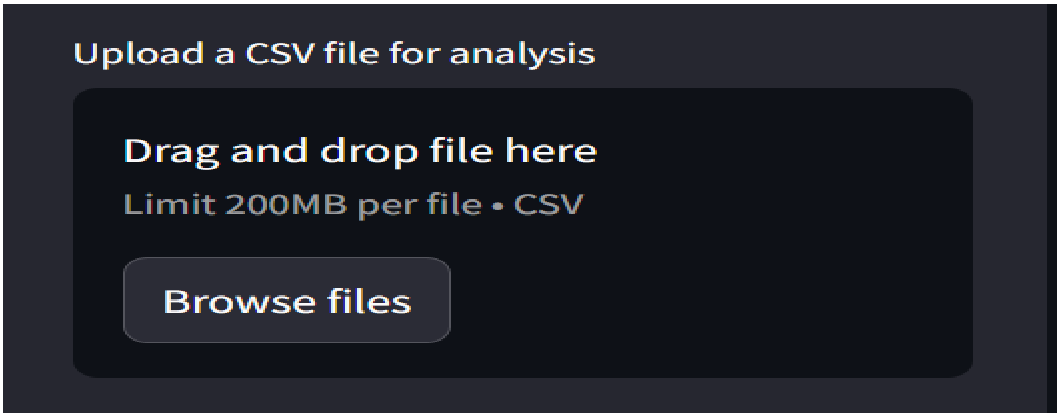
3. Prediction Output Section

- Once the user clicks "Predict Wastage Amount," the predicted amount of food wastage (in kilograms) is displayed with a success message.
- The prediction is intuitive and immediately actionable for the user.



4. Interactive Dashboard Section

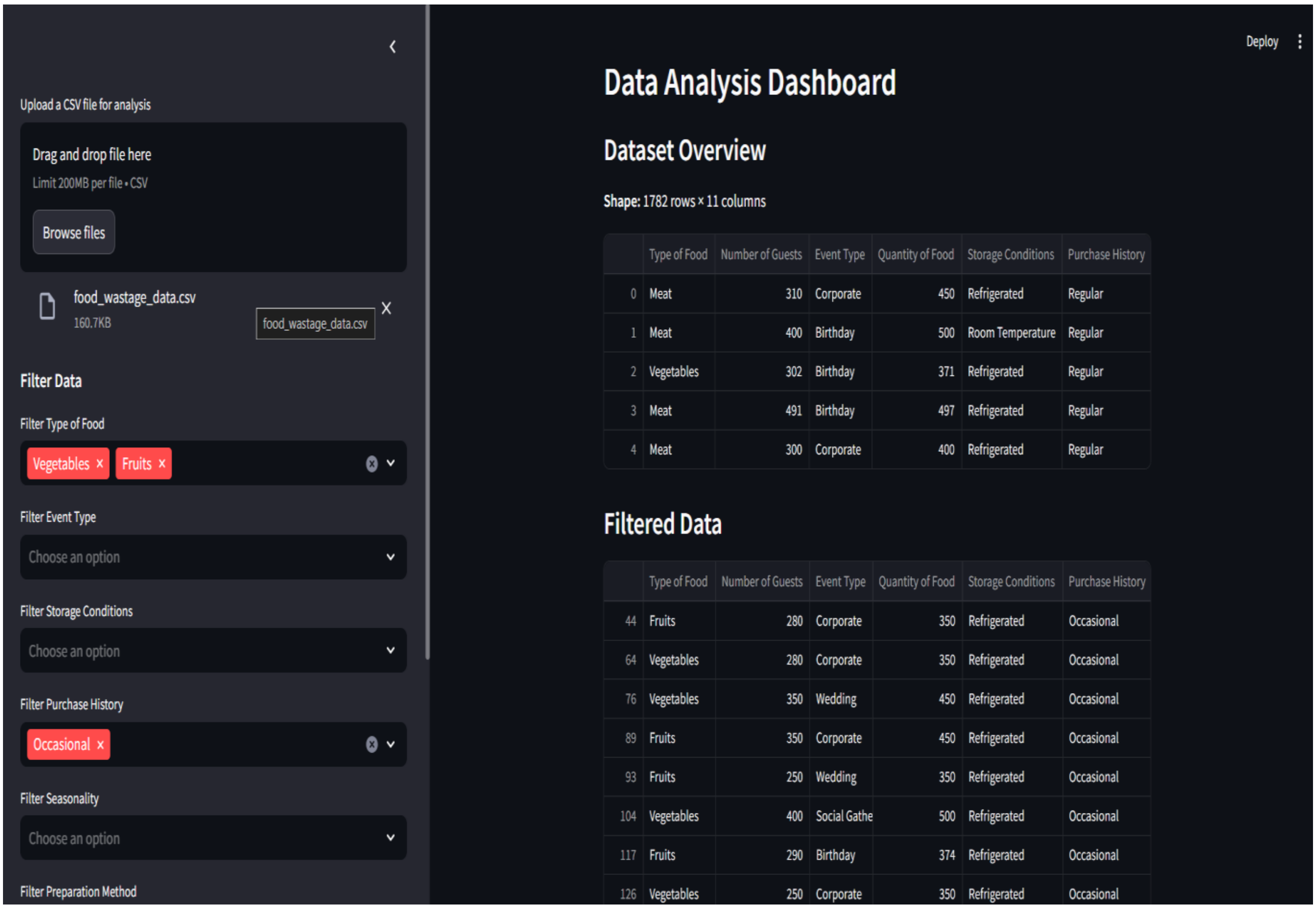
- A separate section supports uploading **CSV files** for bulk data analysis.

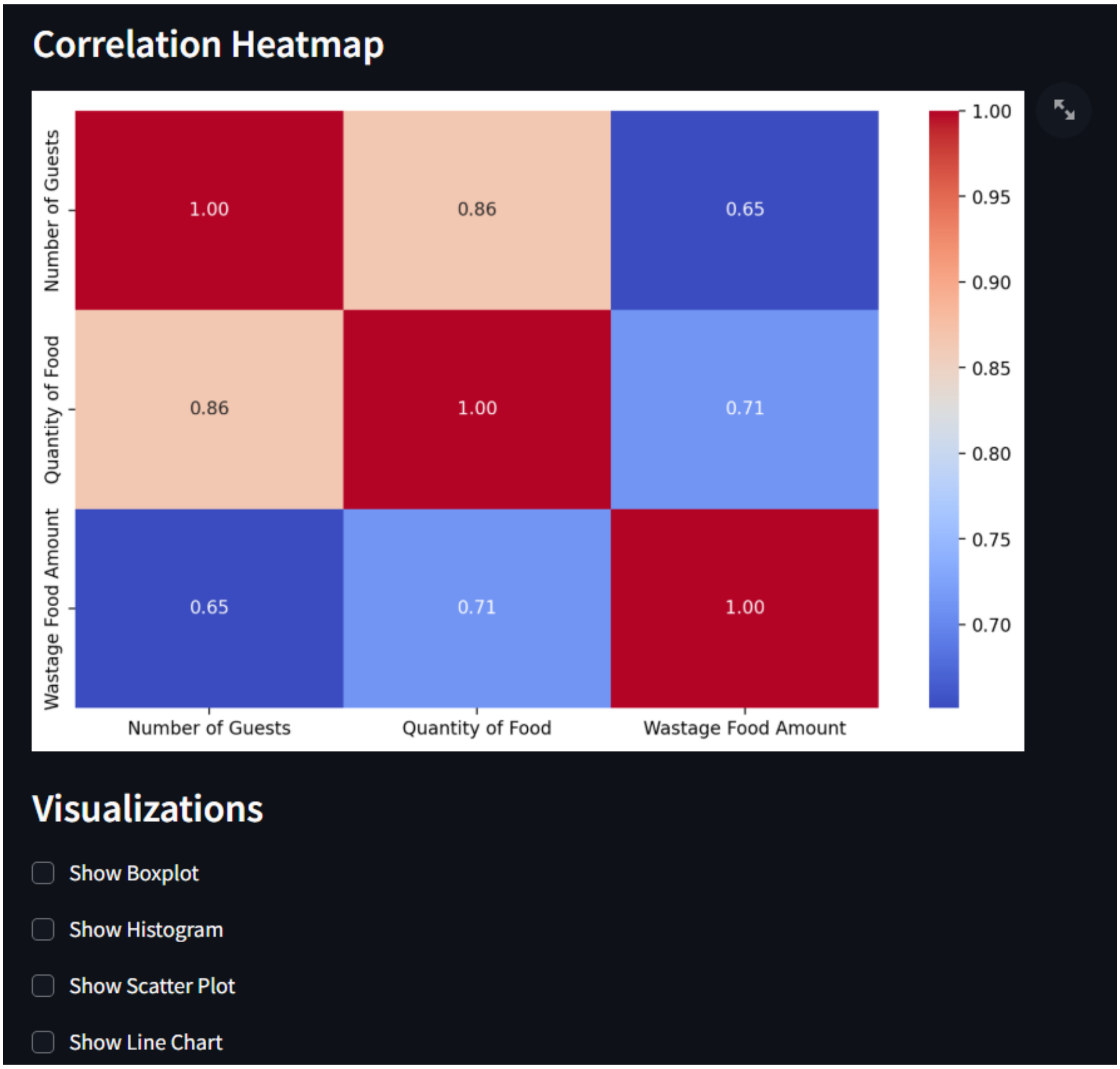


Users can **visualize data** trends using:

- **Bar Charts** to show comparisons (e.g., food wastage by event type).
- **Pie Charts** to represent distributions (e.g., proportion of wastage by food type).
- **Line Graphs** to analyze trends over time (e.g., seasonal variations in wastage).

Additional options for filtering, sorting, and interacting with uploaded data are available for enhanced analysis.




Correlation Heatmap
Number of Guests
Quantity of Food
Wastage Food Amount
1.00
0.86
0.65
0.86
1.00
0.71
0.65
0.71
1.00
Number of Guests
Quantity of Food
Wastage Food Amount
1.00
0.95
0.90
0.85
0.80
0.75
0.70
Visualizations
Show Boxplot
Show Histogram
Show Scatter Plot
Show Line Chart

CONCLUSION AND FUTURE WORK

1 CONCLUSION

The **Food Wastage Prediction and Data Analysis App** successfully integrates machine learning capabilities with interactive data visualization to address the pressing issue of food wastage. Users can predict food wastage based on event-specific details, helping them make informed decisions to reduce waste. Additionally, the data analysis dashboard provides comprehensive insights into datasets, enabling better understanding and decision-making. This project demonstrates the effectiveness of combining predictive modeling and interactive tools for addressing real-world problems like food wastage.

2 ADVANTAGES

- **User-Friendly Interface**: The app provides an intuitive interface for users with minimal technical expertise.
- **Real-Time Predictions**: Offers immediate and accurate predictions of food wastage based on event details.
- **Data-Driven Insights**: The interactive dashboard allows users to explore and analyze datasets effectively, identifying trends and correlations.
- **Flexibility**: The app supports various types of input data and accommodates filtering for tailored analysis.
- **Integration**: Combines predictive modeling and visualization, reducing the need for separate tools.
- **Practical Applications**: Helps event planners, caterers, and organizations minimize wastage and optimize food usage.

3 FUTURE ENHANCEMENT

- Add features like spoilage rates and cultural preferences.
- Expand visualization types (e.g., geospatial maps).
- Include a recommendation system for waste reduction strategies.
- Enable cloud integration and mobile app development.
- Support real-time IoT data and multilingual functionality.

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