A

Semester Project-IV Report

On “Carbon_Footprint_Tracker”

In partial fulfillment of requirements for the degree of

Bachelor of Technology

In Artificial Intelligence and Machine Learning

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[2024-25]

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CERTIFICATE

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Under the guidance of Prof. N. A. Patil in partial fulfillment of the requirement for the degree of Bachelor of Technology in Department of Artificial Intelligence and Machine Learning (Semester- VI) of Dr. Babasaheb Ambedkar Technological University, Lonere during the academic year 2024 - 25.

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ABSTRACT

Climate change stands as one of the most critical global challenges of our time, with carbon emissions being a major contributing factor. Despite its urgency, many individuals remain unaware of their personal carbon footprint and how everyday activities—such as transportation, energy usage, food consumption, and waste management—impact the environment. This lack of awareness poses a significant barrier to the adoption of sustainable lifestyles.

Our project, titled "Carbon Footprint Detection," seeks to bridge this awareness gap by providing a user-friendly, web-based system that enables individuals to calculate and analyze their personal carbon emissions. By allowing users to input data related to their daily habits, the system offers insightful analysis and visualizations oftheir environmental impact. Additionally, it provides personalized recommendations aimed at reducing their carbon footprint. This empowers users to make informed and sustainable choices, ultimately contributing to environmental preservation.

Currently, the global annual carbon footprint has exceeded an alarming 40 billion tons, emphasizing the urgent need for collective action. There is a direct correlation between individual daily habits and the increase in CO_2 emissions. Practices such as energy consumption, transportation, residential heating and cooling, and food production play a significant role in this growing environmental issue. Recognizing the vital role individuals play in climate change mitigation, our project focuses on fostering awareness and encouraging behavioral change.

CHAPTER – 1

INTRODUCTION

Climate change is a pressing global issue, largely driven by carbon emissions from human activities. Many individuals are unaware of how their daily habits—such as transportation, energy use, and food consumption—contribute to their carbon footprint. Our project, "Carbon Footprint Detection," aims to raise awareness and promote sustainable living through a user-friendly web-based system. By inputting lifestyle data, users can calculate their personal carbon emissions and receive tailored recommendations to reduce them. This tool empowers individuals to make informed, eco-conscious choices, encouraging behavior that supports climate change mitigation and fosters a more environmentally responsible society.

In addition to promoting awareness, the application is designed to engage users through interactive features such as monthly tracking, progress reports, and goal setting. These elements not only enhance user experience but also foster long-term commitment to reducing carbon emissions. By combining data analytics with personalized feedback, the project aspires to bridge the gap between knowledge and action.

1.1 Background:

In recent decades, climate change has evolved from a scientific concern to a global crisis, impacting ecosystems, economies, and human health. At the heart of this issue lies the excessive release of greenhouse gases, particularly carbon dioxide (CO_2), primarily generated by human activities such as burning fossil fuels, deforestation, industrial processes, and transportation. The concept of a carbon footprint was introduced to quantify the total emissions of CO_2 and other greenhouse gases attributable to an individual, organization, or product throughout its lifecycle.

While policy changes and industrial reforms are essential, individual actions also play a significant role in combating climate change. Everyday activities —like driving cars, using electricity, consuming animal-based products, and producing household waste—contribute significantly to global carbon emissions. However, a lack of awareness and accessible tools makes it difficult for people to understand the environmental impact of their choices. To bridge this gap, there is a growing need for digital tools that enable individuals to track, evaluate, and reduce their personal carbon emissions. Our project, "Carbon Footprint Detection," responds to this need by providing a user-interactive platform that not only calculates carbon output but also offers practical recommendations. This initiative supports the global push toward sustainability by empowering individuals to make eco-friendly decisions and adopt greener lifestyles, ultimately contributing to a more resilient planet.

1.2 Motivation: The alarming rise in global temperatures, frequent natural disasters, and the increasing concentration of greenhouse gases in the atmosphere have highlighted the urgent need to address climate change. One of the key contributors to this crisis is the carbon footprint generated by human activities. While governments and industries play a crucial role in large-scale mitigation efforts, individual actions collectively have a significant impact. Unfortunately, many people are unaware of how their daily choices contribute to environmental degradation.

This lack of awareness served as the primary motivation for our project, "Carbon Footprint Detection." We recognized the need for a simple, accessible tool that could help individuals understand and take responsibility for their environmental impact. By providing a platform where users can calculate and analyze their carbon emissions, we aim to promote conscious decision-making and sustainable living.

1.3 Problem Statement: Climate change has become an increasingly urgent global concern, with carbon emissions playing a major role in accelerating environmental degradation. While numerous initiatives have been launched at governmental and industrial levels to curb emissions, individual contributions often go unnoticed or unmeasured. Many people are unaware of how their everyday activities—such as commuting, energy consumption, food choices, and waste generation—significantly impact the environment.

This lack of awareness stems largely from the absence of accessible, user-friendly tools that allow individuals to quantify and understand their personal carbon footprint. As a result, there exists a critical gap between knowledge and action. Individuals who wish to adopt environmentally friendly habits often lack the information or motivation to make informed changes in their lifestyles.

The proposed project, "Carbon Footprint Detection," aims to bridge this gap by providing a web-based application that enables users to calculate, analyze, and reduce their carbon emissions. By delivering personalized insights and actionable recommendations based on user input, the system encourages sustainable behavior and helps individuals become active participants in the fight against climate change. This project ultimately seeks to empower users to make eco-conscious decisions and contribute to a more sustainable and responsible global community.

1.4 Objectives of the Work:

The main objective of the "Carbon Footprint Detection" project is to develop a web-based system that enables individuals to calculate, understand, and reduce their personal carbon emissions based on their daily lifestyle choices. The project aims to raise environmental awareness and promote sustainable living by empowering users with actionable insights. The specific objectives of the project are as follows:

1. To design and implement a user-friendly web application that collects data related to users' daily activities such as transportation, energy consumption, diet, and waste generation.
2. To accurately calculate the user's carbon footprint using established environmental data models and emission factors corresponding to the input data.
3. To provide detailed analysis and visualizations of the user’s carbon emissions, making it easier to interpret and understand the environmental impact of their lifestyle choices.
4. To generate personalized recommendations for reducing carbon emissions based on individual user profiles and activity patterns.
5. To encourage behavioral change by promoting awareness and educating users about the environmental effects of their actions.
6. To support sustainability efforts by enabling users to set goals, track their progress over time, and make continuous improvements in reducing their carbon footprint.

CHAPTER – 2

Literature Survey

Understanding and mitigating carbon emissions has become a major focus in environmental research. Numerous studies and digital tools have emerged over the years to help quantify and reduce individual and collective carbon footprints. This literature survey explores the existing research and technological advancements in the field of carbon footprint detection and sustainability awareness.

1. Carbon Footprint Calculation Models:

Several studies have proposed mathematical models and emission factor databases to estimate carbon footprints based on lifestyle factors. The Greenhouse Gas Protocol and IPCC Guidelines for National Greenhouse Gas Inventories have been widely adopted as standard frameworks for emission calculations. These models consider variables such as fuel usage, electricity consumption, travel distance, and food types to provide accurate emission estimates.

2. Digital Tools and Applications:

Web-based platforms like the Carbon Footprint Calculator by the Environmental Protection Agency (EPA) and tools by the World Wildlife Fund (WWF) offer basic functionality to assess individual emissions. However, many of these applications lack interactivity, personalization, or real-time analytics, limiting user engagement and long-term impact.

3. Machine Learning in Carbon Prediction:

Recent research explores the use of machine learning algorithms—such as linear regression, decision trees, and neural networks—to enhance the accuracy of carbon footprint predictions. These approaches help analyze large datasets and predict emissions more efficiently, adapting over time with user behavior.

4. Behavioral Change and Awareness:

According to sustainability research, providing personalized feedback significantly increases the likelihood of users adopting environmentally responsible behavior. Studies emphasize the need for intuitive interfaces and educational content within carbon tracking platforms to maximize impact and retention.

5. Gaps in Existing Solutions:

Despite the availability of various carbon tracking tools, many lack localized recommendations, integration with daily habits, or options for tracking progress over time. Moreover, existing tools often present data in complex formats that are difficult for general users to understand and act upon.

Conclusion:

The literature highlights a growing interest in tools that not only calculate emissions but also encourage sustainable behavior. However, the current gap between carbon awareness and user engagement presents an opportunity for more personalized, user-friendly, and action-oriented platforms. The Carbon Footprint Detection project seeks to address these gaps by combining real-time calculation, data visualization, and actionable recommendations to promote eco-friendly living.

2.2 Limitations in Existing System:

Over the past decade, various carbon footprint calculators and sustainability tracking platforms have been developed by environmental organizations, governments, and research institutions. These limitations are discussed in detail below:

1. Lack of Personalization:

Many existing carbon footprint calculators offer only generalized estimations and suggestions. They fail to consider important individual-specific factors such as location (urban vs. rural), regional emission rates, climate conditions, and lifestyle preferences. As a result, the recommendations provided often do not resonate with users or fit their daily routines, making it difficult for them to take meaningful action.

2. Non-Intuitive and Complex Interfaces:

A significant number of available tools present data in complex tabular forms or use technical jargon that is not easily understood by the average user. This creates a usability barrier, especially for those without a background in environmental science or data analysis. A poor user experience can discourage continued use and prevent widespread adoption.

3. Narrow Scope of Analysis:

Most existing systems primarily focus on two or three areas—commonly electricity usage, transportation habits, and heating/cooling practices. They often exclude or underestimate the impact of other essential factors such as diet (meat vs. plant-based), packaged product consumption, clothing purchases, and waste management. This partial data collection leads to an incomplete and inaccurate representation of a user's total carbon footprint.

4. One-Time Assessments with No Progress Tracking:

Current systems usually provide a single-use analysis, offering no facility for users to track their monthly progress, set goals, or receive updated insights based on changes in behavior. Without continuity or feedback loops, these tools lose their value over time and fail to encourage lasting behavioral change.

5. Lack of Real-Time Feedback and Interactivity:

Another major limitation is the absence of real-time data processing and adaptive feedback mechanisms. Users do not receive immediate suggestions or alerts that could help them modify their behavior as situations change—such as reducing appliance usage during peak hours or choosing low-emission travel alternatives on the go.

CHAPTER – 3

REQUIREMENTS

3. SOFTWARE AND HARDWARE REQUIREMENTS

3.1 Software Requirements

Table 3.1: Software Requirements

Sr. No.	Name of Resource	Specifications
1.	Operating System	Windows 11
2.	Software	HTML,CSS,JS/Streamlit

3.2 Hardware Requirements

Table 3.2: Hardware Requirements

Sr. No.	Name of Resource	Specifications
1.	Processor	Intel I3
2.	Primary Memory	4 GB
3.	Secondary Memory	256 GB SSD

CHAPTER-4

IMPLEMENTATION DETAILS

4. IMPLEMENTATION DETAILS

Phase I: Data Collection and Preprocessing

1. Data Collection

The initial phase focused on gathering data from publicly available datasets related to carbon emissions. Data sources included government databases, research publications, and datasets from environmental organizations. The objective was to collect reliable and diverse data covering various emission-contributing activities.

2. Exploratory Data Analysis (EDA)

- **Data Cleaning:**
- Missing values were handled appropriately, and inconsistencies were resolved. Units of measurement were standardized—for example, converting fuel consumption into equivalent CO_2 emissions.
- **Data Transformation:**
- Emission sources were categorized into major sectors: Transport, Energy, Diet, Waste, and Shopping. Feature engineering techniques were applied to derive meaningful attributes from raw data.
- **Statistical Analysis:**
- The distribution of emissions across various behavioral categories was analyzed to identify trends and patterns.
- **Data Visualization:**
- Graphs and heatmaps were created to visualize emission patterns and facilitate understanding of key contributing factors.

Phase II: Model Training and Evaluation

Multiple machine learning models were trained and evaluated to predict carbon emissions effectively. Fine-tuning was performed to ensure optimal model performance.

- **Linear Regression (LR):**

Used as a baseline model to understand basic dataset relationships.

- **MLP Regressor (Neural Network - NN):**

  Multi-layer perceptron model with hidden layers configured as (64,128,64).

  Activation Function: Tanh (to ensure smooth transitions).

  Max Iterations: 436 (to ensure convergence).

- **Gradient Boosting Regressor (GBR):**

  An ensemble method that combines decision trees.

  Reduces both bias and variance to improve prediction accuracy.

  Final model of choice due to its superior performance in both accuracy and error minimization.

Phase III: Model Performance Analysis and Selection

To evaluate the performance of the trained models, the following metrics were used:

Root Mean Square Error (RMSE):

Measures prediction error; lower values indicate better performance.

R^2 Score:

Represents the proportion of variance explained by the model; closer to 1 indicates better accuracy.

Performance Summary:

Model	RMSE (↓ Lower is better)	R^2 Score (↑ Closer to 1 is better)
Linear Regression (LR)	261.61	0.9341
MLP Regressor (Neural Network)	261.61	0.9341
Gradient Boosting Regressor (GBR)	216.16 (Best)	0.9550 (Best)

Conclusion:

The Gradient Boosting Regressor (GBR) was selected as the final model due to its lowest RMSE and highest R^2 score, outperforming both LR and Neural Network models.

CHAPTER-4

IMPLEMENTATION DETAILS

4. IMPLEMENTATION DETAILS

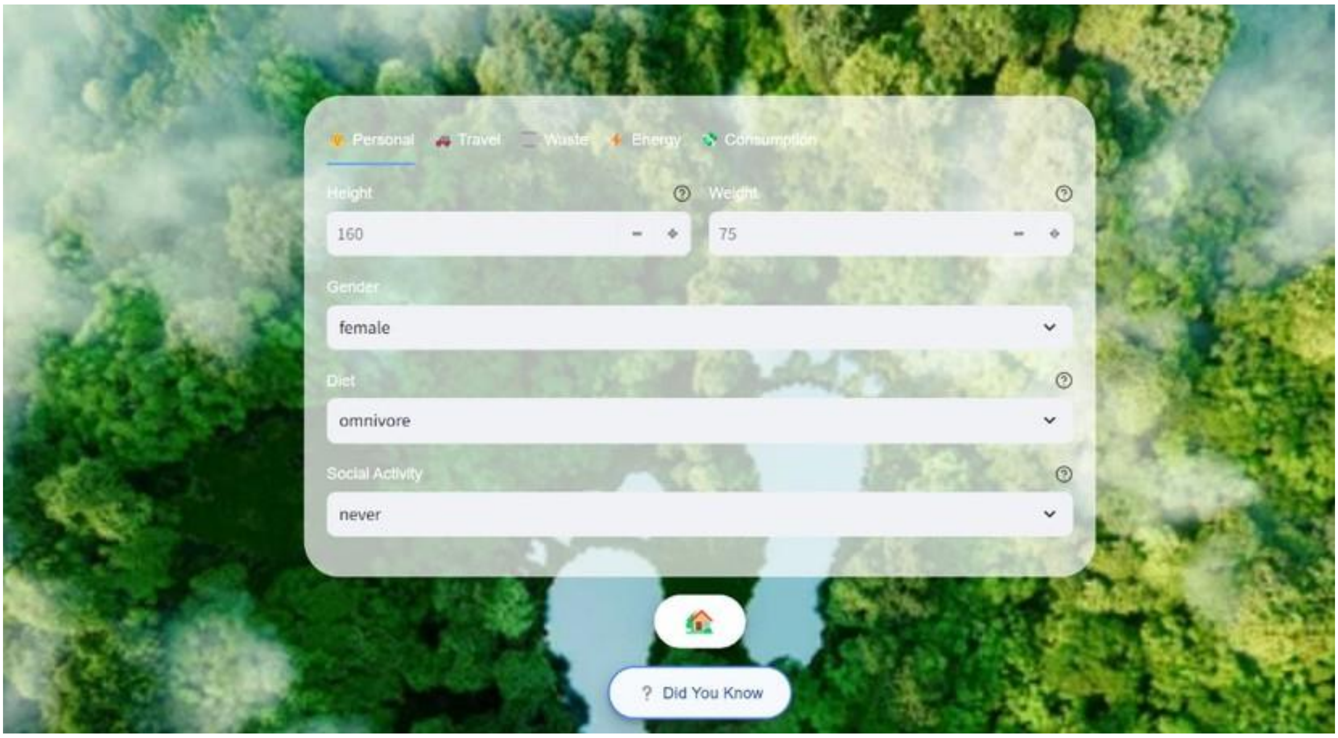
4.1 The function.py code

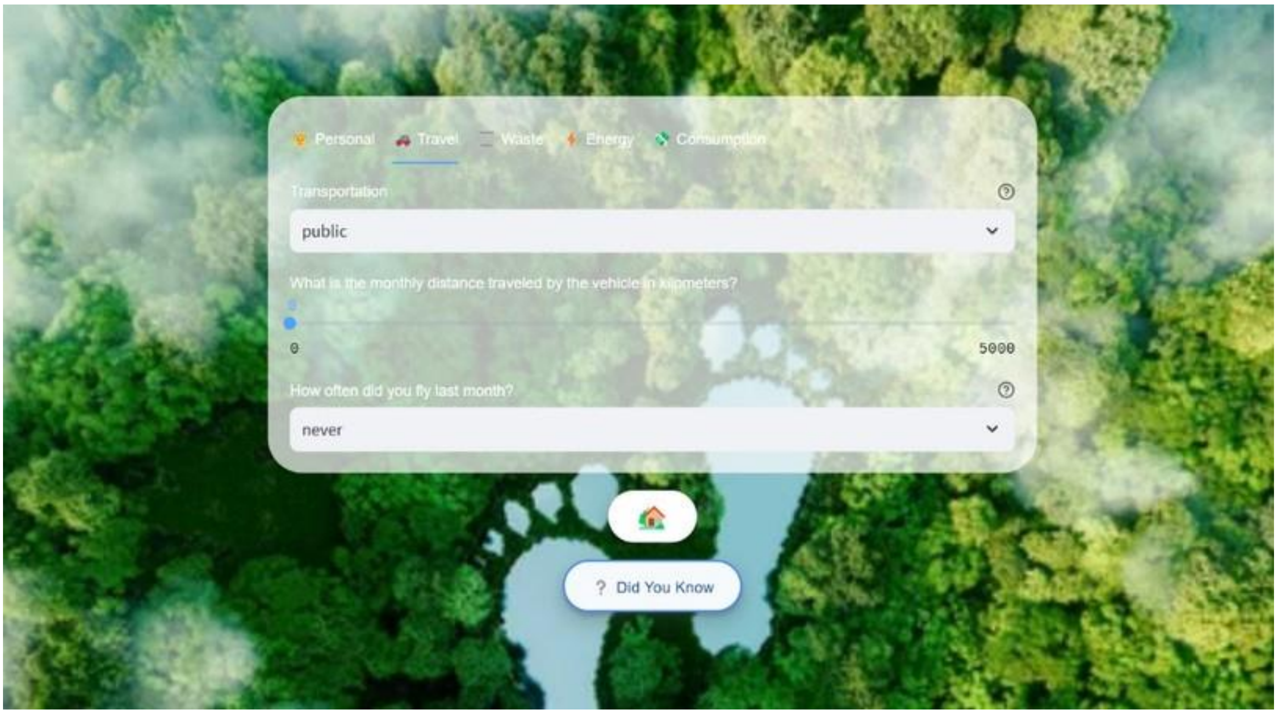
```
from streamlit.components.v1 import html
import numpy as np
from PIL import Image, ImageDraw, ImageFont
import matplotlib.pyplot as plt
import io
import pandas as pd
def click_element(element):
    open_script = f"<script type = 'text/javascript'>window.parent.document.querySelector('[id^=tabs-bui][id$=-
{element}]').click();</script>"
    html(open_script, width=0, height=0)

sample = {'Body Type': 2,
 'Sex': 0,
 'How Often Shower': 1,
 'Social Activity': 2,
 'Monthly Grocery Bill': 230,
 'Frequency of Traveling by Air': 2,
 'Vehicle Monthly Distance Km': 210,
 'Waste Bag Size': 2,
 'Waste Bag Weekly Count': 4,
 'How Long TV PC Daily Hour': 7,
 'How Many New Clothes Monthly': 26,
 'How Long Internet Daily Hour': 1,
 'Energy efficiency': 0,
 'Do You Recyle_Paper': 0,
 'Do You Recyle_Plastic': 0,
 'Do You Recyle_Glass': 0,
 'Do You Recyle_Metal': 1,
 'Cooking_with_stove': 1,
 'Cooking_with_oven': 1,
 'Cooking_with_microwave': 0,
 'Cooking_with_grill': 0,
 'Cooking_with_airfryer': 1,
 'Diet_omnivore': 0,
 'Diet_pescatarian': 1,
 'Diet_vegan': 0,
 'Diet_vegetarian': 0,
 'Heating Energy Source_coal': 1,
 'Heating Energy Source_electricity': 0,
 'Heating Energy Source_natural gas': 0,
 'Heating Energy Source_wood': 0,
 'Transport_private': 0,
 'Transport_public': 1,
 'Transport_walk/bicycle': 0,
 'Vehicle Type_None': 1,
 'Vehicle Type_diesel': 0,
 'Vehicle Type_electric': 0,
 'Vehicle Type_hybrid': 0,
 'Vehicle Type_lpg': 0,
 'Vehicle Type_petrol': 0}
```

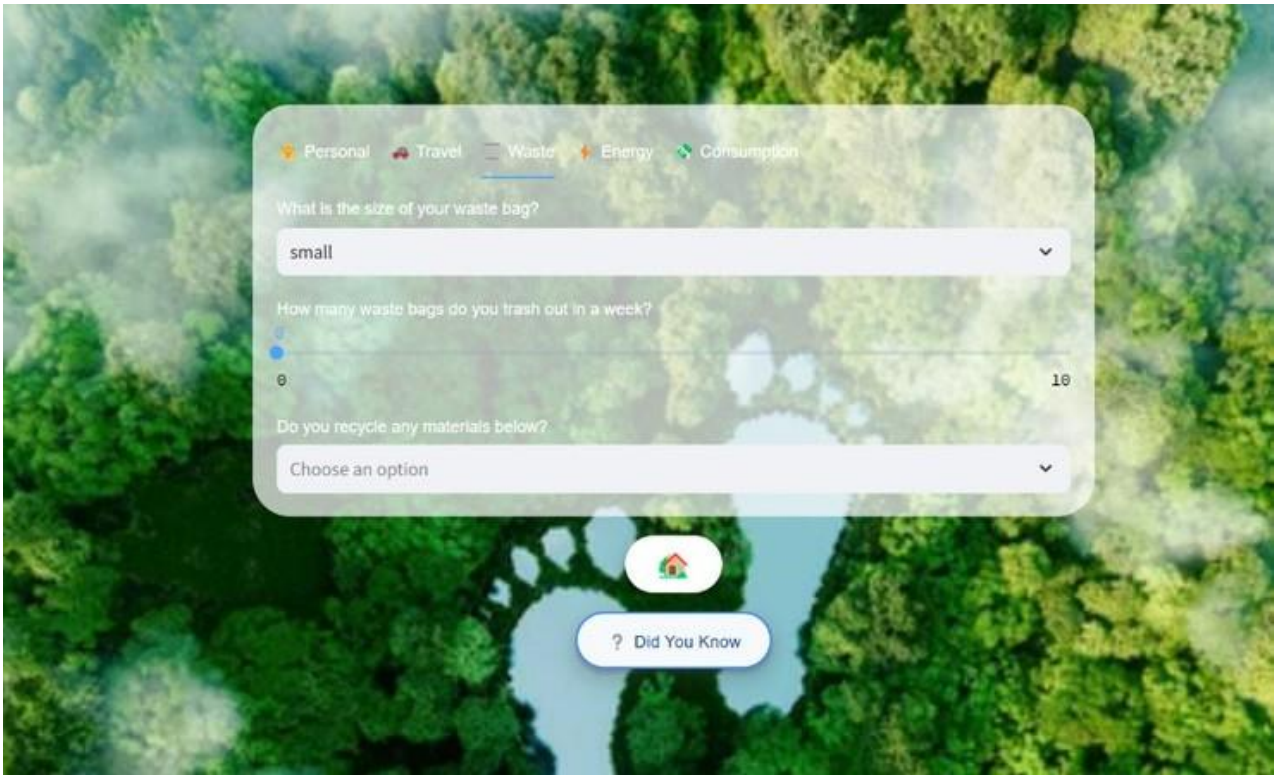
```
def input_preprocessing(data):
    data["Body Type"] = data["Body Type"].map({'underweight':0, 'normal':1, 'overweight':2, 'obese':3})
    data["Sex"] = data["Sex"].map({'female':0, 'male':1})
    data = pd.get_dummies(data, columns=["Diet","Heating Energy Source","Transport","Vehicle Type"], dtype=int)
    data["How Often Shower"] = data["How Often Shower"].map({'less frequently':0, 'daily':1, "twice a day":2, "more frequently":3})
    data["Social Activity"] = data["Social Activity"].map({'never':0, 'sometimes':1, "often":2})
    data["Frequency of Traveling by Air"] = data["Frequency of Traveling by Air"].map({'never':0, 'rarely':1, "frequently":2, "very
frequently":3})
    data["Waste Bag Size"] = data["Waste Bag Size"].map({'small':0, 'medium':1, "large":2,  "extra large":3})
    data["Energy efficiency"] = data["Energy efficiency"].map({'No':0, 'Sometimes':1, "Yes":2})
    return data
def hesapla(model,ss, sample_df):
    copy_df = sample_df.copy()
    travels = copy_df[["Frequency of Traveling by Air",
                         "Vehicle Monthly Distance Km",
                         'Transport_private',
                          'Transport_public',
                          'Transport_walk/bicycle',
                          'Vehicle Type_None',
                          'Vehicle Type_diesel',
                          'Vehicle Type_electric',
                          'Vehicle Type_hybrid',
                          'Vehicle Type_lpg',
                          'Vehicle Type_petrol']]
    copy_df[list(set(copy_df.columns) - set(travels.columns))] = 0
    travel = np.exp(model.predict(ss.transform(copy_df)))

    copy_df = sample_df.copy()
    energys = copy_df[[ 'Heating Energy Source_coal','How Often Shower', 'How Long TV PC Daily Hour',
                         'Heating Energy Source_electricity','How Long Internet Daily Hour',
                         'Heating Energy Source_natural gas',
                         'Cooking_with_stove',
                          'Cooking_with_oven',
                          'Cooking_with_microwave',
                          'Cooking_with_grill',
                          'Cooking_with_airfryer',
                         'Heating Energy Source_wood','Energy efficiency']]
    copy_df[list(set(copy_df.columns) - set(energys.columns))] = 0
    energy = np.exp(model.predict(ss.transform(copy_df)))

    copy_df = sample_df.copy()
    wastes = copy_df[[  'Do You Recyle_Paper','How Many New Clothes Monthly',
                         'Waste Bag Size',
                         'Waste Bag Weekly Count',
                         'Do You Recyle_Plastic',
                         'Do You Recyle_Glass',
                         'Do You Recyle_Metal',
                         'Social Activity',]]
    copy_df[list(set(copy_df.columns) - set(wastes.columns))] = 0
    waste = np.exp(model.predict(ss.transform(copy_df)))

    copy_df = sample_df.copy()
    diets = copy_df[[ 'Diet_omnivore',
                     'Diet_pescatarian',
                     'Diet_vegan',
                     'Diet_vegetarian', 'Monthly Grocery Bill','Transport_private',
                     'Transport_public',
                     'Transport_walk/bicycle',
                      'Heating Energy Source_coal',
                      'Heating Energy Source_electricity',
                      'Heating Energy Source_natural gas',
                      'Heating Energy Source_wood',
                      ]]
    copy_df[list(set(copy_df.columns) - set(diets.columns))] = 0
    diet = np.exp(model.predict(ss.transform(copy_df)))
    hesap = {"Travel": travel[0], "Energy": energy[0], "Waste": waste[0], "Diet": diet[0]}

    return hesap
```

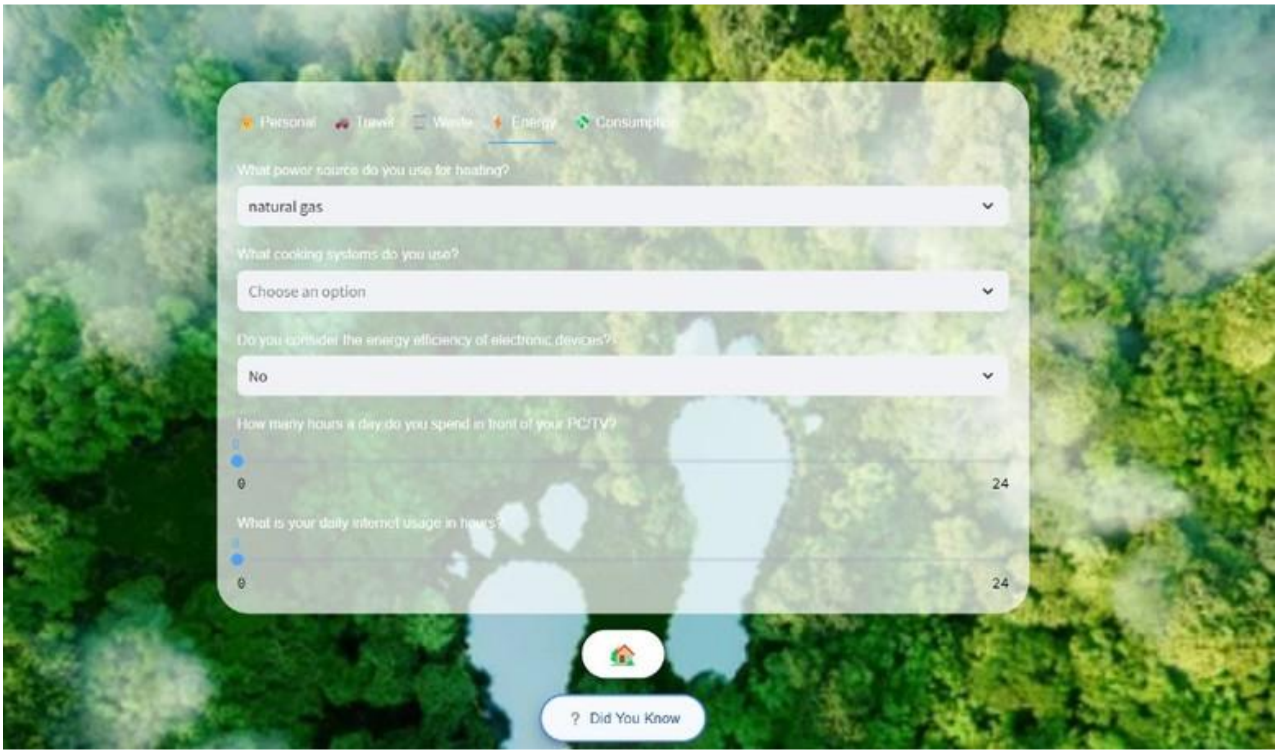
```
def chart(model, scaler,sample_df, prediction):
    p = hesapla(model, scaler,sample_df)
    bbox_props = dict(boxstyle="round", facecolor="white", edgecolor="white", alpha=0.7)

    plt.figure(figsize=(10, 10))
    patches, texts = plt.pie(x=p.values(),
                             labels=p.keys(),
                             explode=[0.03] * 4,
                             labeldistance=0.75,
                             colors=["#29ad9f", "#1dc8b8", "#99d9d9", "#b4e3dd" ], shadow=True,
                             textprops={'fontsize': 20, 'weight': 'bold', "color": "#000000ad"})
    for text in texts:
        text.set_horizontalalignment('center')

    data = io.BytesIO()
    plt.savefig(data, transparent=True)

    background = Image.open("./media/default.png")
    draw = ImageDraw.Draw(background)
    font1 = ImageFont.truetype(font="./style/ArchivoBlack-Regular.ttf", size=50)
    font = ImageFont.truetype(font="./style/arialuni.ttf", size=50)
    draw.text(xy=(320, 50), text=f"  How big is your\nCarbon Footprint?", font=font1, fill="#039e8e", stroke_width=1, stroke_fill="#039e8e")
    draw.text(xy=(370, 250), text=f"Monthly Emission \n\n   {prediction:.0f} kgCO₂e", font=font, fill="#039e8e", stroke_width=1, stroke_fill="#039e8e")
    data_back = io.BytesIO()
    background.save(data_back, "PNG")
    background = Image.open(data_back).convert('RGBA')
    piechart = Image.open(data)
    ayak = Image.open("./media/ayak.png").resize((370, 370))
    bg_width, bg_height = piechart.size
    ov_width, ov_height = ayak.size
    x = (bg_width - ov_width) // 2
    y = (bg_height - ov_height) // 2
    piechart.paste(ayak, (x, y), ayak.convert('RGBA'))
    background.paste(piechart, (40, 200), piechart.convert('RGBA'))
    data2 = io.BytesIO()
    background.save(data2, "PNG")
    background = Image.open(data2).resize((700, 700))
    data3 = io.BytesIO()
    background.save(data3, "PNG")
    return data3
```

Welcome Front Page:




Personal
Travel
Waste
Energy
Consumption
Transportation
public
What is the monthly distance traveled by the vehicle in kilometers?
0
5000
How often did you fly last month?
never
Did You Know


Personal
Travel
Waste
Energy
Consumption
What is the size of your waste bag?
small
How many waste bags do you trash out in a week?
0
10
Do you recycle any materials below?
Choose an option
Did You Know


Personal
Travel
Waste
Energy
What power source do you use for heating?
natural gas
What cooking systems do you use?
Choose an option
Do you consider the energy efficiency of electronic devices?
No
How many hours a day do you spend in front of your PC/TV?
0
24
What is your daily internet usage in hours?
0
24
? Did You Know


How big is your Carbon Footprint?
Monthly Emission
536 kgCO₂e
Energy
Travel
Waste
Diet

Conclusion:

Climate change poses an ever-growing threat to our planet, driven largely by increasing carbon emissions from human activities. While large-scale policy and industrial interventions are critical, individual contributions to reducing carbon footprints are equally important. However, a major barrier to individual action is the lack of awareness and accessible tools to understand personal environmental impact.

The project titled "Carbon Footprint Detection" was developed to address this challenge. It provides a user-friendly, web-based platform that enables individuals to calculate their carbon emissions based on various lifestyle inputs, such as transportation, energy consumption, diet, waste management, and shopping habits. The application employs machine learning models to analyze the data and generate accurate carbon footprint estimations. Among the models tested—Linear Regression, MLP Regressor, and Gradient Boosting Regressor—the Gradient Boosting Regressor (GBR) outperformed the others, achieving the lowest Root Mean Square Error (RMSE) and the highest R^2 Score.

In addition to emission calculation, the system offers visual insights and tailored recommendations to guide users toward more sustainable behaviors. This promotes not only awareness but also long-term engagement with eco-friendly practices.

In conclusion, the Carbon Footprint Detection system successfully demonstrates how technology can be leveraged to support climate action at the individual level. By empowering users with knowledge and actionable feedback, the project contributes meaningfully to the broader goal of environmental sustainability and responsible living.

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