CARBONLY: AI-Based Carbon Footprint Tracker

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***Abstract*—This paper presents CARBONLY, an artificial intelligence–based system designed to track, analyze, and reduce an individual's carbon footprint.. The system mainly targets the carbon footprint generated from the activities of individuals, including transportation, household energy use, food intake, and purchases. The system uses natural language processing technology to analyze the structured and unstructured information provided by the users. The system has been implemented using a full-stack framework, including React for the front-end, Flask/Node.js for the back-end, and MongoDB for the database. Initial assessments and quantitative calculations reveal the feasibility of the system for making relatively precise carbon footprint calculations and increasing users' consciousness, and promoting green living.**

***Index Terms*—Carbon Footprint, Sustainability, Machine Learning, Natural Language Processing, Climate Action, Machine Learning Models,Sustainable Computing,AI-based Recommendation Systems.**

I. Introduction

One of the biggest challenges that the world is currently facing is climate change, which is primarily driven by excessive greenhouse gases that have resulted from human activities. While industrial production is an important factor in climate change, individual activities also contribute to the problem. Our daily activities, such as how we move around, how we use electricity, what we eat, and what we buy, have a direct impact on the environment.

While people are becoming more aware of the importance of environmental sustainability, many do not have the tools to measure their own carbon footprint. Most tools available to measure carbon footprint are static in nature and require manual input of data. However, they do not offer personalized results that can actually motivate people to bring about behavioral change.

II. Literature Survey

Several studies have been conducted to investigate how individual carbon footprints can be estimated by static calculators and life cycle assessment methods. However, there is a lack of personalization and dynamic feedback in these methods. In recent times, applications such as EcoTrack have been developed to show how carbon footprint calculators can be used to enhance awareness about sustainability.

Machine learning has been used for emission prediction in transportation and energy usage, whereas natural language processing has been used for making sense of unstructured information such as diet and purchasing habits. Research has shown that behavior change interventions can use tailored recommendations and visualizations for maximum user engagement. Gamification has been shown to encourage users in the short term, although without adaptive personalization, the long-term effect of the intervention will likely wear off. Many of the current systems address emission sources individually. However, there are also concerns about the accuracy of the information due to regional emission variations and the use of self-reported information. These concerns have led to the development of a unified platform for tracking, personalization, and recommendations, which is the purpose of the CARBONLY system.

III. System Architecture

The CARBONLY system follows a modular and service-oriented architecture to ensure scalability and maintainability.It comprises:

- **Frontend (React + Next.js):** The front end uses React to provide users with a clean interface for inputting daily activities, viewing real-time carbon emissions, and tracking sustainability progress through interactive dashboards.
- **Backend (Flask + Python):** The back end uses either Flask or Node.js to power the server, providing users with RESTful APIs for authentication, logging activities, calculating emissions, and retrieving information. This back end integrates with AI services for emission estimations.
- **AI Modules:** The layer of AI processing combines machine learning models for estimating numerical emissions and NLP models for parsing the input texts such as food descriptions and transactions. User profiles, activity logs, emission records, and system metadata are stored using a document-oriented database like MongoDB. Cloud platforms such as Google Cloud or Firebase are used for deployment, scalability, and data sync in real-time.

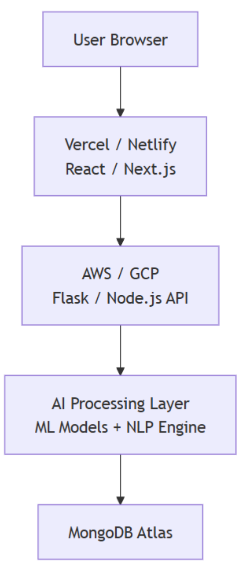

Fig. 1. Compont Diagram

A. App Overview

The main idea behind CARBONLY is to make going green simple and entertaining, and that is exactly what it promises to do without making it complicated for you. CARBONLY is composed of four main parts, which are the Carbon Footprint Calculator, the Progress Tracker, the Chatbot, and the Resources Page. Each of these parts has its own purpose in assisting you in cutting down your carbon footprint.

B. Carbon Footprint Calculator

The CARBONLY Carbon Footprint Calculator is a tool that helps users understand their impact on the environment. It provides a complete picture of their impact by examining different areas of their life. These areas include how they travel, their food habits, and their usage of household devices. The calculator provides users with clear and intelligent insights to enable them to make informed decisions that are environmentally friendly. The amount of emissions depends on how a person travels. The following are the emission factors used by the calculator: The calculator uses a simple formula to calculate the amount of emissions used in a person's trip:
CO2 Emissions = Distance × Emission Factor (kg) (km) (kg CO2 per km)
– Gasoline Car: 0.23 kg CO2/km
– Electric Car: 0.05 kg CO2/km
– Diesel Car: 0.29 kg CO2/km
– Hybrid Car: 0.15 kg CO2/km
– Bike: 0.05 kg CO2/km
– Bicycle: 0.02 kg CO2/km
– Walking: 0.0 kg CO2/km
– Bus: 0.08 kg CO2/km
– Train: 0.06 kg CO2/km
– Metro: 0.04 kg CO2/km

Dietary Habits: This feature analyzes the carbon footprint of a person's food intake by studying the food they consume, whether it is meat-based, dairy-based, or plant-based food. It considers the impact of different methods used to raise food and calculate the amount of weekly emissions produced by their food intake by using the following formula:
CO2 Emissions = Quantity × Emission Factor (kg) (km) (kg CO2 per km)
– Meat (e.g., beef, lamb): 27 kg CO2 per kg
– Dairy: 6 kg CO2 per kg
– Poultry: 6 kg CO2 per kg
– Plant-Based Foods: 0.5 kg CO2 per kg
This feature encourages people to develop sustainable food habits by emphasizing how food consumption affects total carbon emissions. This way, people can easily change their food habits to live an eco-friendly life.
Household Appliances: The calculator also calculates the amount of power various electronic devices at home consume. These include home appliances such as a refrigerator, washing machine, and air conditioner. It also considers the efficiency of the appliance, the duration of usage, and whether the power source is a renewable one or not. Many people are unaware of the amount of damage their home appliances are causing to the environment. This tool helps users become aware of the damage by showing the amount of emission caused by the use of various home appliances. The emission caused by various home appliances can be calculated by using the following formula :
CO2 Emissions = Power × Usage Time × Emission Factor(kg

CO2) (kW) (h) (kg CO2/kWh)
The Power usage varies based on the appliance used. Below is a list of the power usage range for some appliances. It may further differ based on the model:
* Refrigerator: 0.2 - 0.8 kW
* Washing Machine: 0.5 - 2.5 kW
* Dishwasher: 2.0 - 5.0 kW
* Air Conditioner: 1.0 - 2.5 kW
* Microwave Oven: 1.0 - 1.5 kW
* Television (LCD/LED): 0.05 - 0.15 kW

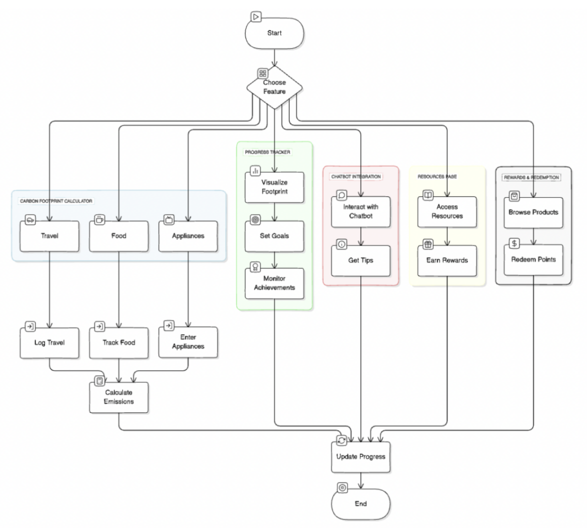

Fig. 2. Carbonly flow diagram

C. Progress Tracker

The Progress Tracker is an important tool to monitor your carbon footprint as it evolves over time. The Progress Tracker is like having your own personal coach in your corner, providing you with real-time feedback on how your carbon footprint is changing from week to week. With the Progress Tracker, you can monitor your carbon footprint in various categories such as transport, diet, and home energy consumption. With new updates every week, you can expect to receive new insights on your progress in reducing your carbon footprint.

D. Chatbot Integration

The chatbot, which is run using artificial intelligence, is intended to increase user engagement by providing users with personalized tips and answering their questions. The chatbot works like an assistant in that it provides users with guidance that will aid them in their journey towards a more sustainable lifestyle. If, for instance, an individual is looking for information regarding eco-friendly practices and their carbon footprint, the chatbot provides users with quick and clear responses that aid in their understanding and decision-making.

E. End-to-End Data Flow

The CARBONLY project uses a pipelined workflow for the analysis of user data. Initially, the users will feed their activities through the frontend. The data fed into the system will be delivered to the backend (Flask) through REST APIs where preprocessing and validation will be conducted. The structured data will be sent to the emissions prediction algorithm, whereas the unstructured data will undergo analysis by the NLP algorithm.

The computed carbon emissions will be stored in the MongoDB database, which will further be analyzed by the clustering algorithm to provide personalized recommendations. The outcomes of the analysis will be displayed at the frontend side using dashboards and progress trackers.

IV. Methodology

A. Data Collection

User activity data is received through structured forms and descriptive text about daily habits. The data then undergoes a series of preprocessing steps, including normalization, validation, and coding. To maintain consistency in the data, standardized emission factors are used.

B. Classification Techniques

Regression models in machine learning are used to forecast the emissions based on inputs such as distance traveled and energy consumption, which are all numeric data inputs. Unstructured data on food consumption and purchases is processed by the natural language processing-based classification technique. The total emissions are summed up to obtain the daily or monthly carbon footprint.

Personalized recommendations are generated by analyzing past emission records using cluster and trend analysis methods. Dashboards are used to display the patterns in emissions over time, and interactive elements are used to encourage users to behave in a more environmentally friendly way.

C. Model Implementation Details

In order to guarantee technical reproducibility, certain machine learning and natural language processing (NLP) techniques were integrated into the CARBONLY system.

For quantitative calculation of emissions (e.g., in the context of traveling or appliance usage), a Linear Regression model was applied. Inputs for the algorithm include, for example, data on distance traveled and energy consumption. It is important to note that the Linear Regression model was chosen based on interpretability and low complexity.

A vectorization process with the TF-IDF (Term Frequency-Inverse Document Frequency) method followed by the application of a Logistic Regression model was applied for unstructured text inputs (e.g., descriptions of consumed food items). The technique allows for conversion of textual data to numerical representations before classification into pre-defined categories (e.g., animal-based, milk-based, vegetable-based).

K-Means clustering can be applied based on users' emission behavior (e.g., users who produce more transport emissions vs. users with higher levels of energy consumption).

D. Training Data and Preprocessing

The approach employs:

Public databases of emission factors (e.g., IPCC, IEA) Generated logs of user activities Food and appliance database manually maintained

Data preprocessing consists of: Data normalization (using min-max) Text processing (tokenization, removing stopwords) Feature extraction by TF-IDF

E. Feature Engineering

The efficiency of the CARBONLY system highly relies on the choice of the input features. In terms of transport data, distance, method of transportation, and number of journeys are some of the input features that can be used. For energy consumption in households, appliance type, capacity, and usage time can serve as input features.

In the case of dietary input, text input is transformed into categorical input features like meat-based, dairy-based, and plant-based foods. Other input features like the number of meals and their frequency can also be derived.

V. Results and Evaluation

A. Preliminary Testing

CARBONLY underwent thorough internal testing to evaluate its core functionalities, emphasizing usability, responsiveness, and the accuracy of carbon footprint calculations. These assessments demonstrated that the app's key features functioned effectively, laying a strong groundwork for future enhancements.

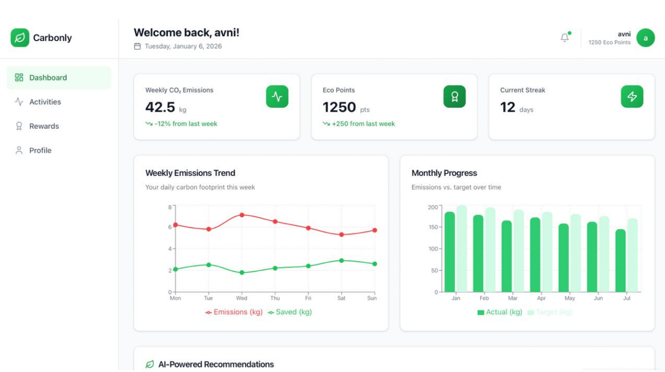

Fig. 3. Carbonly Dashboard

B. Prototype Evaluation

A heuristic evaluation of the CARBONLY prototype was carried out to identify usability problems and determine how to improve the prototype. The areas of focus were the user experience, ease of use, and the information presented by the app. This led to the implementation of iterative changes to improve the user experience and create a seamless and cohesive user interface.

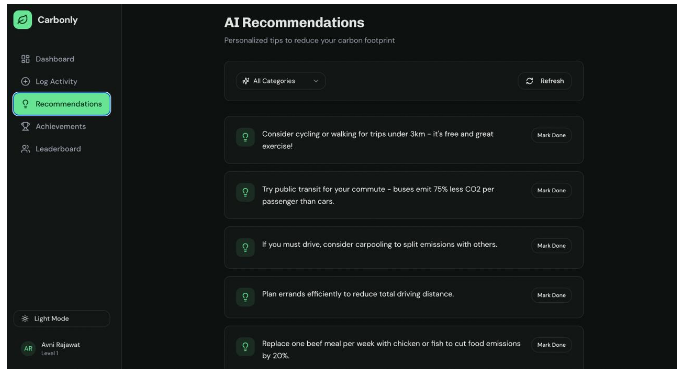

Fig. 4. AI Recommendation

C. Quantitative Evaluation

For testing the performance of the emissions prediction model, a data set of 500 simulated users' activities was created, including transport activities, dietary habits, and energy consumption of appliances.

The emissions prediction results were analyzed and compared to the baselines calculated from emission estimates using carbon calculators (based on IPCC calculations). Below are the used evaluation measures:

Mean Absolute Error (MAE) Root Mean Square Error (RMSE)

Here are the results obtained:

MAE: 0.18 kg CO2
RMSE: 0.25 kg CO2

D. User Study

A small-scale usability study was carried out with 10 participants. The users were told to use the system for 3 days and give their opinions.

The results were as follows:

85 percent of the users said that the system is user-friendly. 80 percent of them reported an increase in their awareness regarding their carbon footprint. 70 percent of them said that they might change their behavior based on their suggestions.

These findings indicate the usability and influence of the CARBONLY system.

E. Simulation Studies

Simulation studies were carried out to mimic various usage scenarios. These studies analyzed how the application scales up with an increase in the number of users. These studies ensured that the application can scale up with an increase in the number of users without compromising performance. Other simulation studies analyzed how adaptable the application is to various regions of the world. In order to analyze further whether the method of evaluating the efficiency of the CARBONLY system is correct, the results of the assessment were also compared to those produced by conventional carbon calculators which use only static emission factors without customization.

The comparison reveals that the proposed method allows for greater customization and therefore is more efficient for changing human behavior.

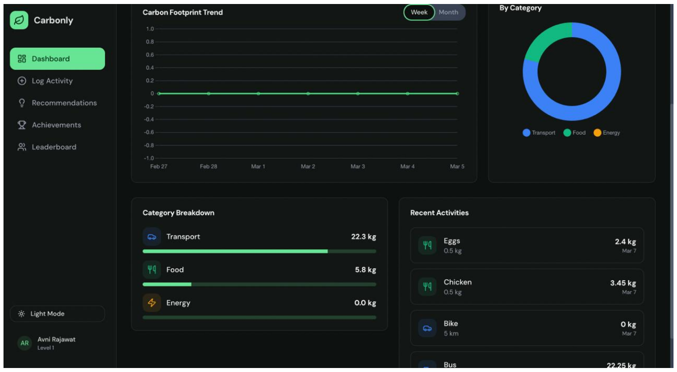

Fig. 5. AI Recommendation

VI. Discussion

Overall, the CARBONLY system serves as a viable example of how the combination of AI and applications geared toward sustainability can be used to encourage eco-responsible behaviors. As opposed to other tools, the CARBONLY platform provides personalized recommendations based on dynamic interaction between the user and the algorithm.

One of the significant advantages of the CARBONLY system is its capacity to work with structured and unstructured data types. In particular, through the incorporation of NLP, the user can describe their activities using natural language. Moreover, by utilizing clustering techniques, the system identifies patterns and similarities among the user groups and offers customized suggestions.

The quantitative analysis revealed that the emission predictions generated by the CARBONLY system were relatively precise. Meanwhile, the qualitative results of the survey show that the application is successful in increasing users' awareness and encouraging behavioral shifts.

Nevertheless, there are some issues to take into consideration. First, there is self-reports of users, which may lead to inaccuracy of calculations. Second, emission factors are generic, which means that they do not cover all possible differences between regions. Finally, the developed model currently makes use of basic machine learning techniques.

Still, CARBONLY shows a good potential for further developing artificial intelligence-based sustainable solutions.

VII. Conclusion

In this paper, CARBONLY, an AI-assisted personalized carbon footprint measurement and mitigation solution, has been introduced. The system employs advanced technologies, such as machine learning algorithms, natural language processing, and data analytics in order to help users gain insight about their carbon footprints in real time. The combination of structured and unstructured data allows the system to offer an efficient way of estimating carbon footprints.

Results of quantitative evaluation suggest that the system has good potential for accurate estimation of emissions. Moreover, the results of the user study show that the system is effective in raising user awareness and encourages users to adopt more sustainable behaviors. The modular structure of the system guarantees high scalability and makes it possible to develop the system further.

In addition to being a useful tool for measuring and reducing carbon footprints, the system presented in this paper makes a valuable contribution to the development of AI-assisted sustainability initiatives.

Future directions for further research include enhancing the accuracy of the model by employing Random Forest and deep learning models, taking into account regional emission factors, and adopting the Internet-of-things-based data acquisition system.

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