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Carbonwise: Smart Carbon Footprint Tracking and Reduction System

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Abstract

Carbon footprint is described as the total emissions of greenhouse gases primarily composed of carbon dioxide caused by humans, a group of individuals, or any other activity. Greenhouse gases are generated through a variety of activities including the use of electrical energy, transportation, consumption of products, production of foods, and others. Tracking the carbon footprint is important since it identifies the source of emissions and methods through which they can be minimized. Our system called CarbonWise involves the creation of a web application that would calculate and track an individual's carbon footprint depending on the activities undertaken on a daily, weekly, or monthly basis. This would be done based on data related to greenhouse gas emissions that have been calculated in various studies and would involve calculations of greenhouse gas emissions of electricity, heating, transport, diet, and waste. We have also incorporated a machine learning algorithm that analyzes previous behavior and provides customized recommendations for reducing greenhouse gas emissions. Recommendations can range from adopting renewable energy sources, optimizing travel, and reducing the use of single-use items. In order to enhance user engagement and foster healthy competition among users, the website incorporates gamification elements that allow users to establish environmental objectives and track their achievements. Through simplifying climate data and providing practical guidance, our system enables individuals to contribute to emission reduction efforts on a global scale.

Keywords: Carbon Tracking, Sustainability, ML Insights, Behaviour Analysis, Eco Decisions, Gamification

1. Introduction

The carbon footprint is used to describe the amount of GHG emissions (mainly CO 2 emissions) generated by individuals, organizations or processes. Individual level surveillance aids in behaviour change and it is an element of larger mitigation actions [1]. CarbonWise is a web-based program, whereby individuals are able to record their daily activities and the data is converted to the respective quantities of CO 2 using the emission factors. It creates interactive dashboard on the results and generates personal recommendations on how to reduce the CO 2 level on the basis of machine learning [3]. The app can be used with a variety of logging options (day/week/month) and it also uses third party information (maps, weather, receipts, etc.) and includes some gamification to encourage continued use.

1.1 Problem Definition

In the new age, sustainability efforts give greater focus to the individual behaviour to lower GHG emissions, yet the issue is that the majority of the population lacks the necessary tools to evaluate and monitor their own carbon footprint. The personal daily activities like transportation, energy consumption, food, heating, and garbage can significantly impact the carbon footprint [8]. Nevertheless, no effective way can help an individual to measure the amount of his/her carbon emission and to identify high-emission practices [6]. Although people have increased awareness of the problem of climate change, the intention-action gap is still present because the carbon calculators are inaccurate, and are founded on the surveys and averages, instead of actual behaviour or region-specific practices [5].

To overcome this problem, the proposed CarbonWise application will be a smart activity-based carbon tracking application that will be able to translate any data that a user keyed into it into the estimated carbon dioxide emissions using emission factors that have been shown to be valid. In contrast with the current products, CarbonWise will continuously track the behavior of the user, adapt to it and analyze previous records of activity. High-impact sources of emissions, setting behavioral patterns, and providing advice, based on the user-specific needs, will be determined using machine learning. CarbonWise will enable users to identify their carbon hot spots, learn how they impact on their carbon profiles and receive guidance on what to do to decrease them using easy-to-use dashboards and visual monitoring tools. The application has the ability to make environmental sustainability a reality by utilizing data and individual analysis.

1.2 Existing Applications

With regard to the current carbon footprint tracking solutions, there are some shortcomings. The conventional calculator systems based on the interface of the websites of such organizations as WWF and EPA require the user to enter fixed data and the emission factors, and provides them with imprecise results without taking their behavior and dynamics into account. Conversely, mobile apps such as Oroeco and JouleBug do offer daily tracking with simple algorithms and not-precise enough forecasts because they have a limited area of expertise. Lastly, software like Sphera and Carbon Trust are not exactly user-friendly, and need more sophisticated configuration than a single user can provide. The above issues provide the reason why an intelligent solution such as the CarbonWise should be implemented.

1.3 Proposed Application

The existing techniques lack a smart ecosystem of tracking carbon, which CarbonWise addresses by integrating scientifically credible computation and machine learning algorithms with behavioral analysis, gamification, and multi-category carbon tracking into a single system. It enables calculation of user activities on-the-go, based on energy consumption, commutes, diet and lifestyle habits, and is accomplished through machine learning algorithms to identify patterns in user behavior and forecast a change in lifestyle behaviors that would positively affect them. Incorporating gamification and goal setting makes CarbonWise a smart behavior platform that enable individuals and organizations to examine and reduce their environmental impact.

2. Literature Survey

"EcoTrack: A Carbon Footprint Tracking and Analysis App" by L. Yadav et al., creates an app on mobile devices to track the use of electricity, transportation and waste generation at home and offer individualized recommendations and contests [1]. This app enhances the awareness and behavior of users, however, it does not solve some problems with high-end analytics, IoT connectivity, and local emission factors.

"Machine Learning Applications for Carbon Emission Estimation" by H.S. Alnuaimi et al., proposes to apply the machine learning methods such as Random Forest, Gradient Boosting, and Neural Networks in the estimation of carbon emission in transport, industrial and energy sectors using energy logs, traffic flow, etc. [2]. Its benefits are that it is more accurate than statistical methods, it can be used to monitor and manage online, but it has a few disadvantages, including the inadequacy of data and a lack of knowledge on models.

"Machine Learning-Based Carbon Emission Predictions In Chinese Provinces" by S. Hong et al., proposes a province-wide forecasting strategy that uses SVM, Random Forest, and Deep Neural Network approaches via training on socio-economic, energy, and industrial data [3]. It outperforms classical regression models not only in short and long-term predictions but also because it is capable of identifying regional differences by using deep learning technology whereas it is limited by imbalanced data and lacks real-time information feeds.

"An Analysis of the Compatibility Between Popular Carbon Footprint Calculators with National Inventory Reports" by E. Arif, A.A. Sharan, and W. Mabee, compares three carbon calculators used by the public to the National Inventory Report of Canada in order to measure consistency [4]. It reveals that there are some differences between emission factors and methodologies that are not standardized, making household emissions measurements unreliable.

"Carbon Footprint Tracking Apps: The Spillover Effects of Feedback and Goal-Activating Appeals" by W. Lasarov et al., focuses on the effect of immediate feedback and goal-setting strategies on sustainable behavior via Carbon Footprint Tracking Apps [5]. As demonstrated in this paper, personalization of feedback and realistic goal-setting have a significant positive impact on emission levels and the lack of the steady spill-over effect and the constant need to participate make it unsustainable.

"Carbon Footprint Tracking Apps: How Effective is Behaviour-Specific Feedback?" by S. Hoffmann et al. explains the effects of the CO 2 feedback of specific sections such as food and transportation on its users [6]. The results show that the concerned knowledge can be applicable towards achieving effective emission savings in the short run but not in the long run due to low motivation.

"Do People Respond to the Climate Impact of Their Behaviour? Evidence from a Carbon Footprint App" by T.R. Fosgaard et al., confirms the reaction of users to real-time carbon dioxide information available in a mobile application, a study referred to as Evidence of a Carbon Footprint App [7]. The research indicates that the presence of the correct emissions information will result in adequate changes in food, travel, and energy-related behaviors, but these changes will slowly fade away due to the desensitization process

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“Analysing the Indicators and Associated Recommendations of Household Emission Calculators” by C. Alexopoulos et al., discusses the continuation of 19 carbon footprint calculators in terms of their scope, emission factor, and recommendation [8]. It is highly variable, has unsubstantiated general recommendations, and lacks a methodology. It concludes that poor standardization is a barrier to their validity and comparability.

3. Design and Methodology

CarbonWise system is designed as an architectural style engineered architecture based on modular, scalar, and personalizable data. This section will be about what’s in the carbonWise app, the carbonwise system, data model, movement flows, and the suggestions engine, which uses machine learning. The use of ML diagrams to describe the design of the system is also mentioned. The method that they use to design is allowing you to add an activity logger, emission calculator, user analytics, dashboard, and even a machine learning recommendation module.

3.1 Technologies Used

An eclectic mix of technologies was embraced to provide performance, scalability and ease of maintenance:

Hardware Requirements

- Minimum Requirements (User Access): Any modern device (laptop, tablet, or smartphone) with a web-browser and good internet connection, with a minimum of 2 GB RAM to operate smoothly.
- Development Requirements: Backend system of 8 GB RAM and machine learning, and dependencies and local database of at least 20 GB.
- Optional (Advanced ML): Hardware capable of training and using advanced machine learning models, which is also GPU-enabled.

Software Requirements

- Frontend: Next.js, Tailwind CSS for style, and Chart.js for data visualization
- Backend and Database: Supabase PostgreSQL, RESTful API integration Next.js API
- API Testing: Postman to test and debug API. Machine Learning: Python 3.10 or later with libraries such as scikit-learn, pandas, numpy, and XGBoost to model recommendations and joblib to serialize models
- Development and Deployment Tools: Version control (CI/CD optional) Git and GitHub, containerization Docker, and development environment Visual Studio Code (VS Code).

3.2 Development Process

CarbonWise is a website which repeatedly modulizes basis in order to make reports, understand and improve real -time carbon footprints. It uses data and information and provides personal suggestions for improvements and scaling through:

Requirement Gathering: By understanding the individual user's needs and insights, we have clearly defined the requirements for the system. We also considered previous carbon footprint calculators and their weaknesses.

System Design: The system is made up of a multi-layer architecture comprising of UI Layer, Application Layer and the Data Layer

Module Implementation:

- The Activity Management Module has been created to gather data from user input users in areas like transport, electricity, food (meat consumption), and garbage management
- The Emission Calculator is a standard calculator which uses proven factorsto calculate users' activities into equivalent carbon footprint units/CO2 units to enable the user to understand their emissions.
- The Dashboard and Visualization Moduleis the one that integrates charts and graphs to show the user their total emissions, their specific category distributions as well as the users trends for improved UX and insights.
- Machine Learning Recommendation Engine: Used K-means clustering and Random Forest/Gradient Boosting techniques to understand user patterns and recommend emission-reduction methods accordingly.
- Gamification Module: Inclined with features like setting goals, achieving streaks, and earning badges to boost user involvement and sustainability practices.
- Authentication and User Management: Secured user access, session management, and data mapping based on the specific users.

Database Integration: A Supabase PostgreSQL database was implemented to store structured informati on about users, their activities, broadcasts and recommendations, enabling faster queries and regular upd ates. for storing structured information about users, their activities, emissions, and recommendations, all owing faster queries and regular updates.

Testing: Functionality, integration and performance tests were carried out on each module, namely loggi ng user activities, calculating emissions, updating dashboards and generating personalized suggestions. i ntegration, and performance tests were performed on each module, namely logging users' activities, calc ulating emissions, updating dashboards, and generating personalized suggestions.

Deployment and Feedback: The solution was deployed as a web application with API based frontend/backend integration. rolled out as a web app with API-based frontend/backend integration. User feedback confirmed the reliability, accuracy of emissions calcu lation, and effectiveness of personalized suggestions generated by the machine learning model. precision of the emissions calculation, and the effectiveness of personalized suggestions generated by the machin e learning model.

3.3 System Design

The CarbonWise system's architecture is based on a clear engineering process that emphasises modula design, ability to scale, intuitiveness, and tailored suggestions based on data. The current chapter gives aan overview of the system's architecture, data model, main interaction paths, and recommendation engine, which uses ML algorithms to work.

3.3.1 System Architecture

The overall architecture of the CarbonWise system is shown in Figure 1. The architecture involves the user interface (UI), backend modules, machine learning algorithm engine, third-party data sources, and database. The UI receives all the user input in the web application. The backend modules use those user activities to perform different functionalities in the system, including activity management, emission calculator, gamification module, and recommender engine.

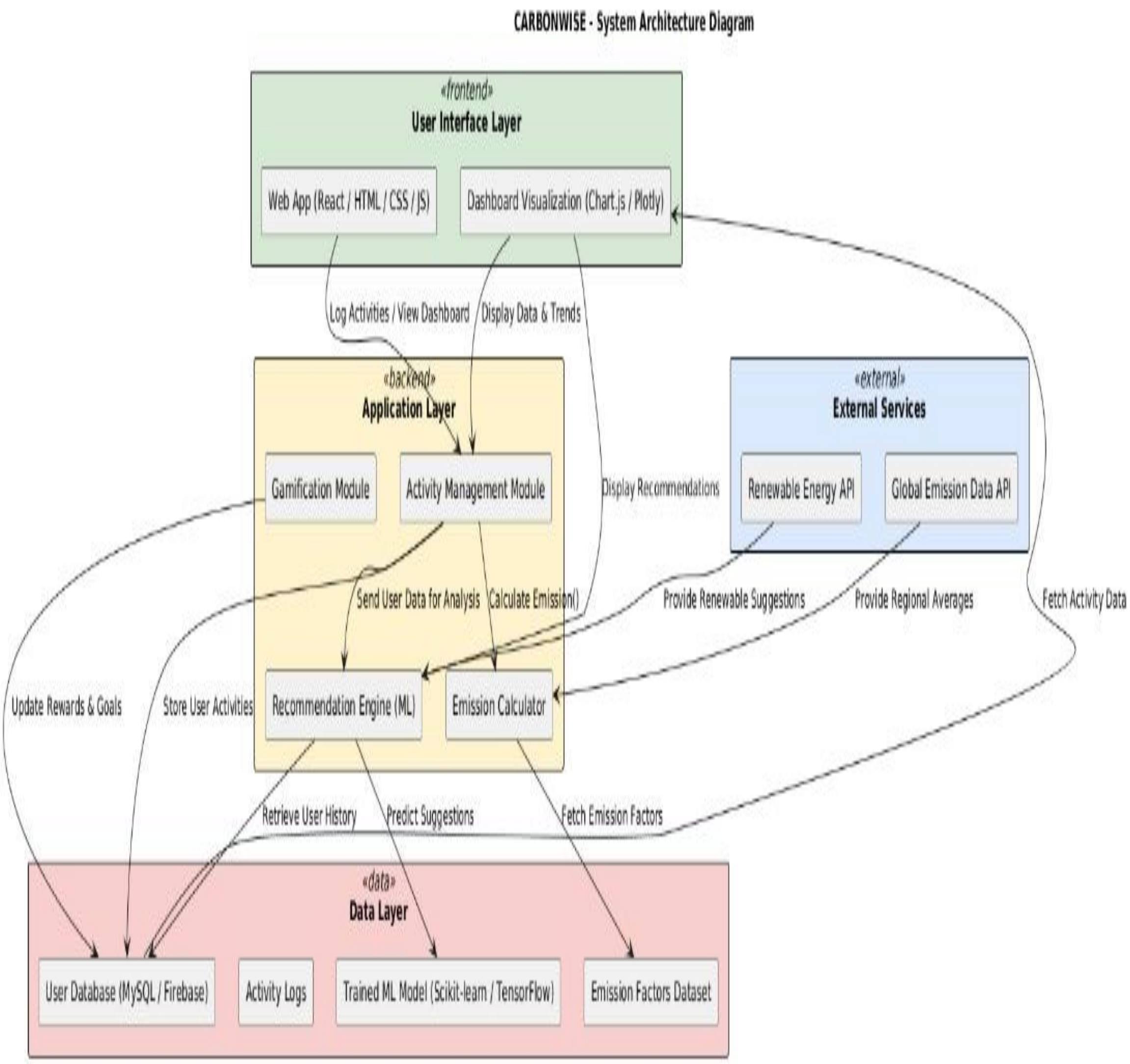

Figure 1: System Architecture Diagram of CarbonWise

3.3.2 Class Diagram

A class diagram of CarbonWise shows the proper handling of data and voluntary user information which includes activity logs, emission factors, data from the dashboard, and personalized suggestions:

Primary Classes Include:

- User - for authentication, preferences, goals
- ActivityLog - category, amount of activity, emissions calculated
- Dashboard - aggregated emission behaviors
- EmissionCalculator - logic for emissions calculations and mappings
- RecommendationEngine - ML algorithm for generating recommendations based on user activity
- GamificationModule - badges, rewards, and progress handling

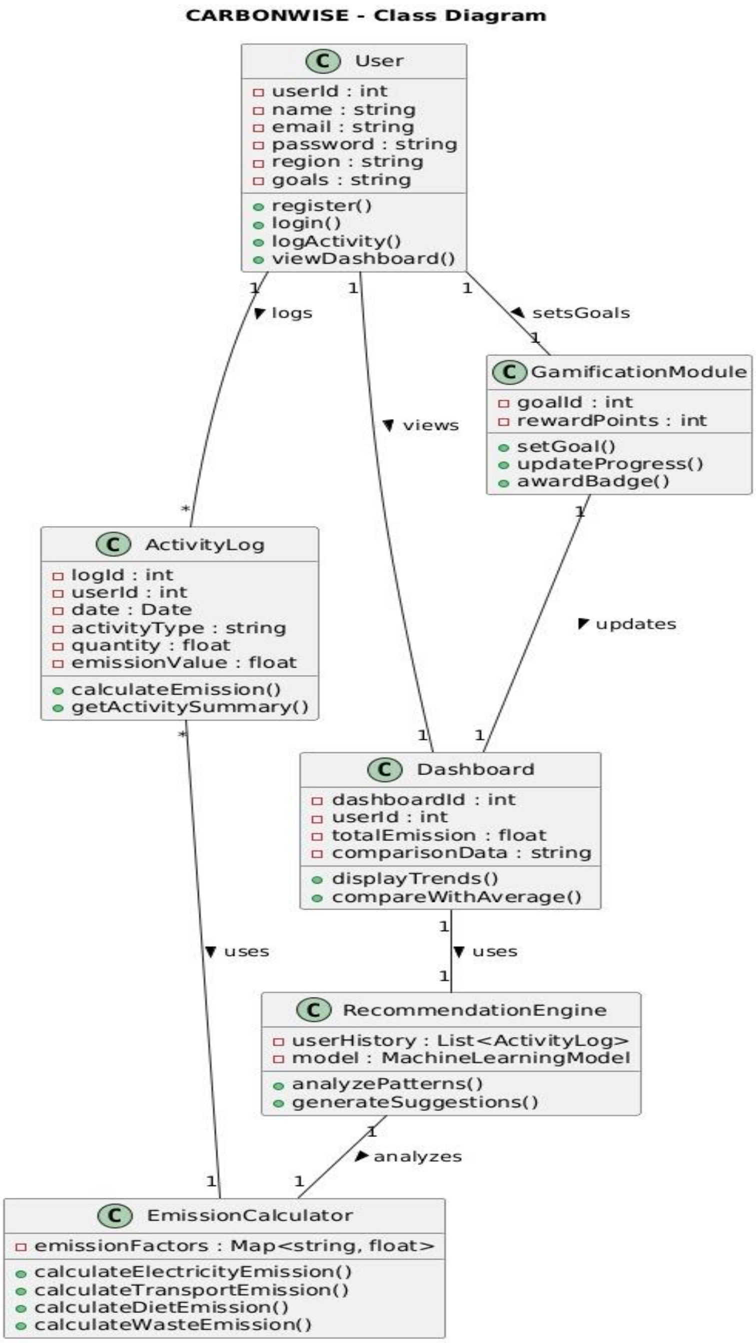

Figure 2: Class Diagram of CarbonWise

The diagram is the class diagram and it illustrates the system's classes, attributes and how they interact with each other.

The second figure showcases the object-oriented architecture of CarbonWise. This incorporates every class and their attributes and methods.

3.3.3 Sequence Diagram

CarbonWise system's sequence diagram is designed for a step-by-step process that any user follows while interacting with the system. It basically highlights the interaction with a general user and the system. This specific diagram shows the pathway from logging activities to getting personalized suggestions. This diagram is specifically useful for highlighting the interactions between UI, backend service, databases and the ML modules.

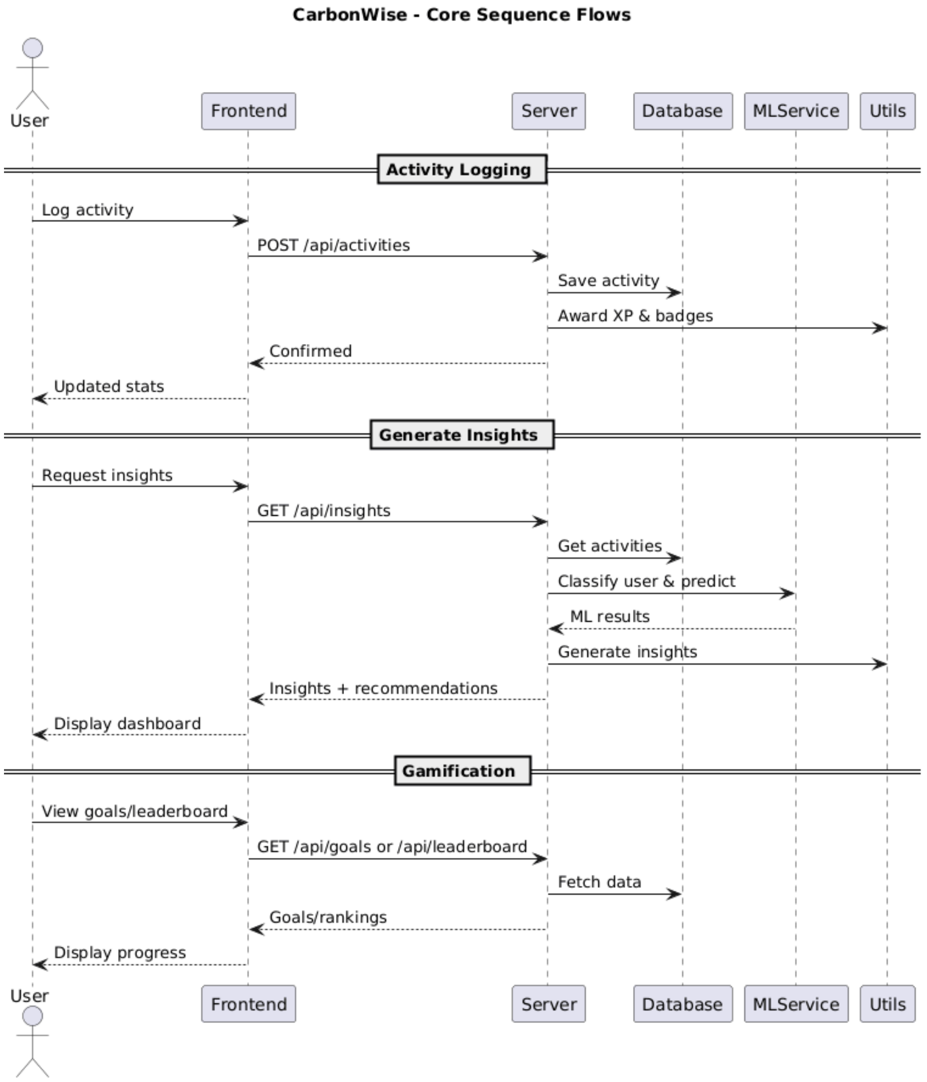

Figure 3: Sequence Diagram of CarbonWise

Figure 3 is the Sequence Diagram which shows the entire process, beginning with the login page, followed by activity logging, calculation of emmisions, updating the dashboard, and generating suggestions.

Various different actions follow each other in the back-end, which includes emission facto lookup, storage of logs, user history analysis asnd suggestion generation have also been illustrated.

3.3.4 Activity Flow The diagram lays out the entire journey a general user might trake when using the website. It starts with launching the website, then the user moves through logging in, entering/logging

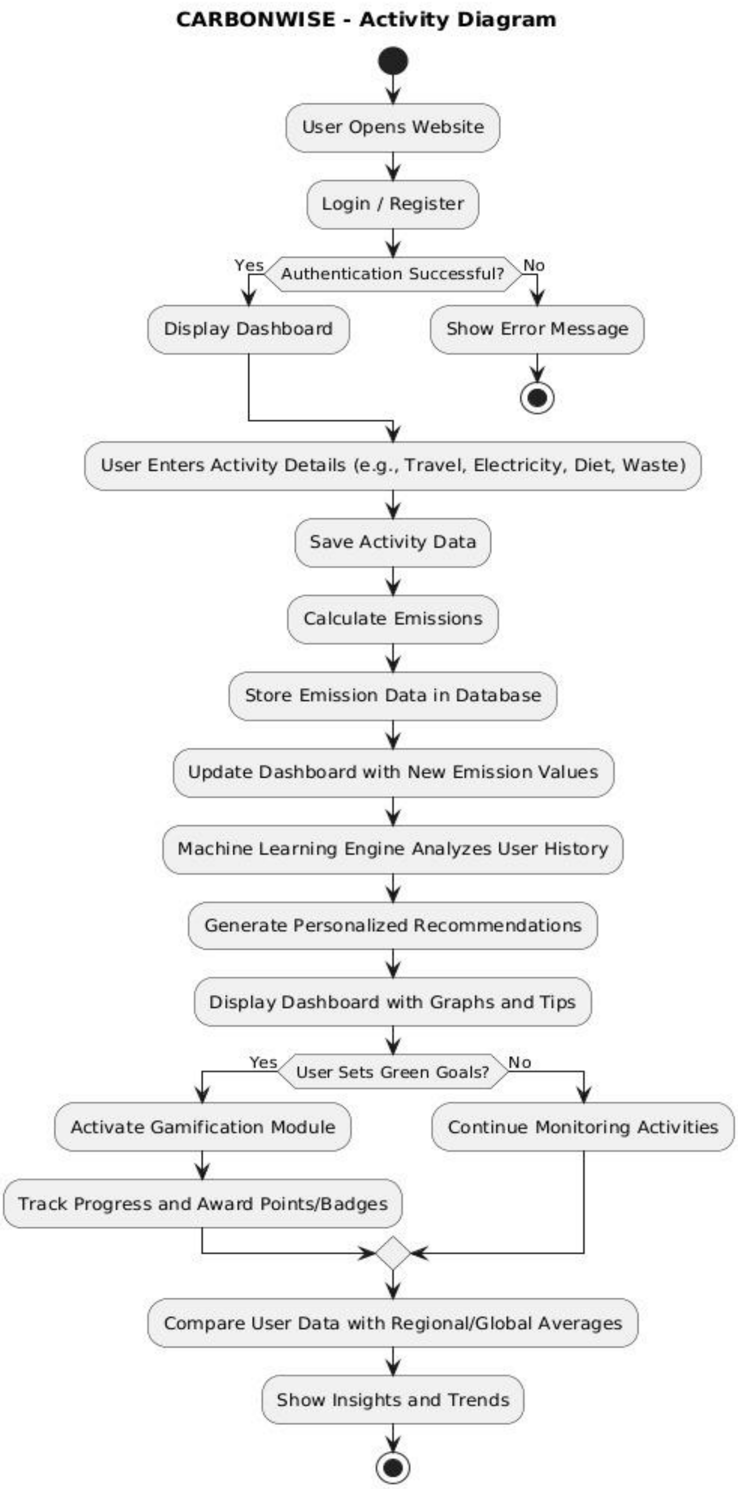

Figure 4: CarbonWise's Activity Diagram

their activities, the system calculating emissions, updating the dashboard, and finally giving personalized suggestions. Users can either set their own goals or simply monitor their carbon footprint. This diagram also shows where people make choices, and how the system interacts with users. We can see how different parts of the system all connect and work together to make everything run smoothly.

The fourth figure shows the entire path any general user follows. It also incorporates goal setting, rewarding, and comparing the individual results with regional values as well as their own vLues across a certain time-frame.

3.3.5 Use Case Diagram

The Use Case diagram depicts all the interconnections taking place between the user, the system, and the machine learning component. Some of the key players of the system include:

● User – The person who logs his/her activity and analyses insights
● Machine Learning Component – Analyzes past data and provides recommendations

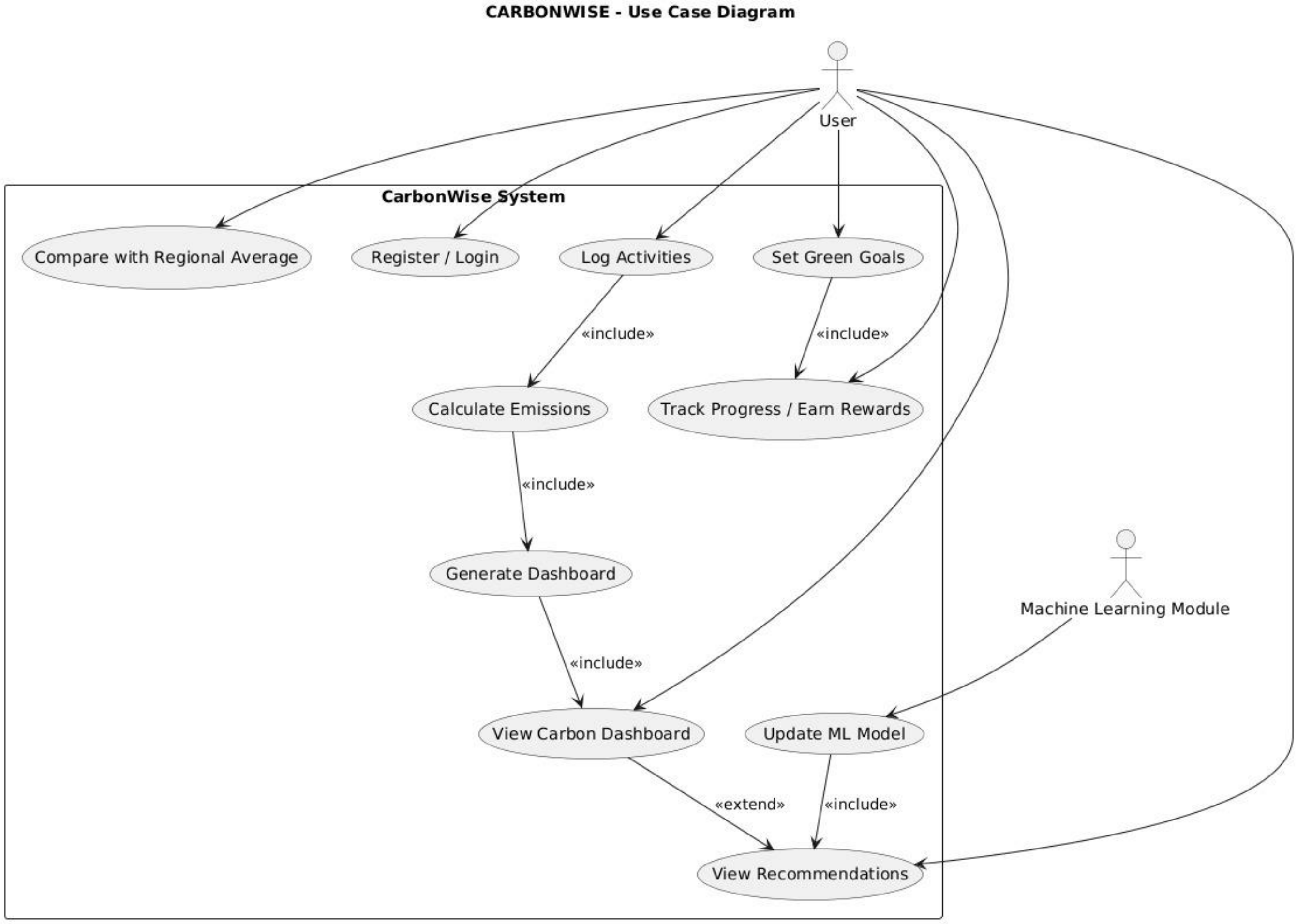

Figure 5: Use Case diagram of CarbonWise

Some of the functionalities depicted through Figure 5 include Register/Login, Log Activities, Calculate Emissions, Create Dashboard, compare with regional average, Monitor Progress, and Receive Recommendations. Contribution from the ML component includes updating user-based models and providing suggestions.

3.3.6 Machine Learning Recommendation Engine Design

The recommendation engine generates suggestions for the users to achieve their sustainability goals. The main components include:

1.Data Preprocessing Module

- Transforms log data into numerical feature vectors
- Determines behavioural factors including high-emissions activities, frequency of certain behaviours, and seasonality

2. Clustering (K-Means)

- Categorizes users by lifestyles such as commute, diet, energy, and others
- Commute Heavy, Diet Heavy, Energy Heavy, etc.

3. Prediction Engine

Calculates what behaviour changes can result in highest CO_2 reduction via Random Forest or Gradient Boosting

4. Recommendation Engine

Provides recommendations to change behaviour including reducing red meat consumption, cutting down on private transportation, or making appliances more efficient.

5. Feedback Mechanism

- Retrains the model after users change their behaviours by logging new activity
- The layering of ML modules and rule-based logic helps the user guarantee accurate, personal and interpretable results, which they can actually utilize in their daily lives.

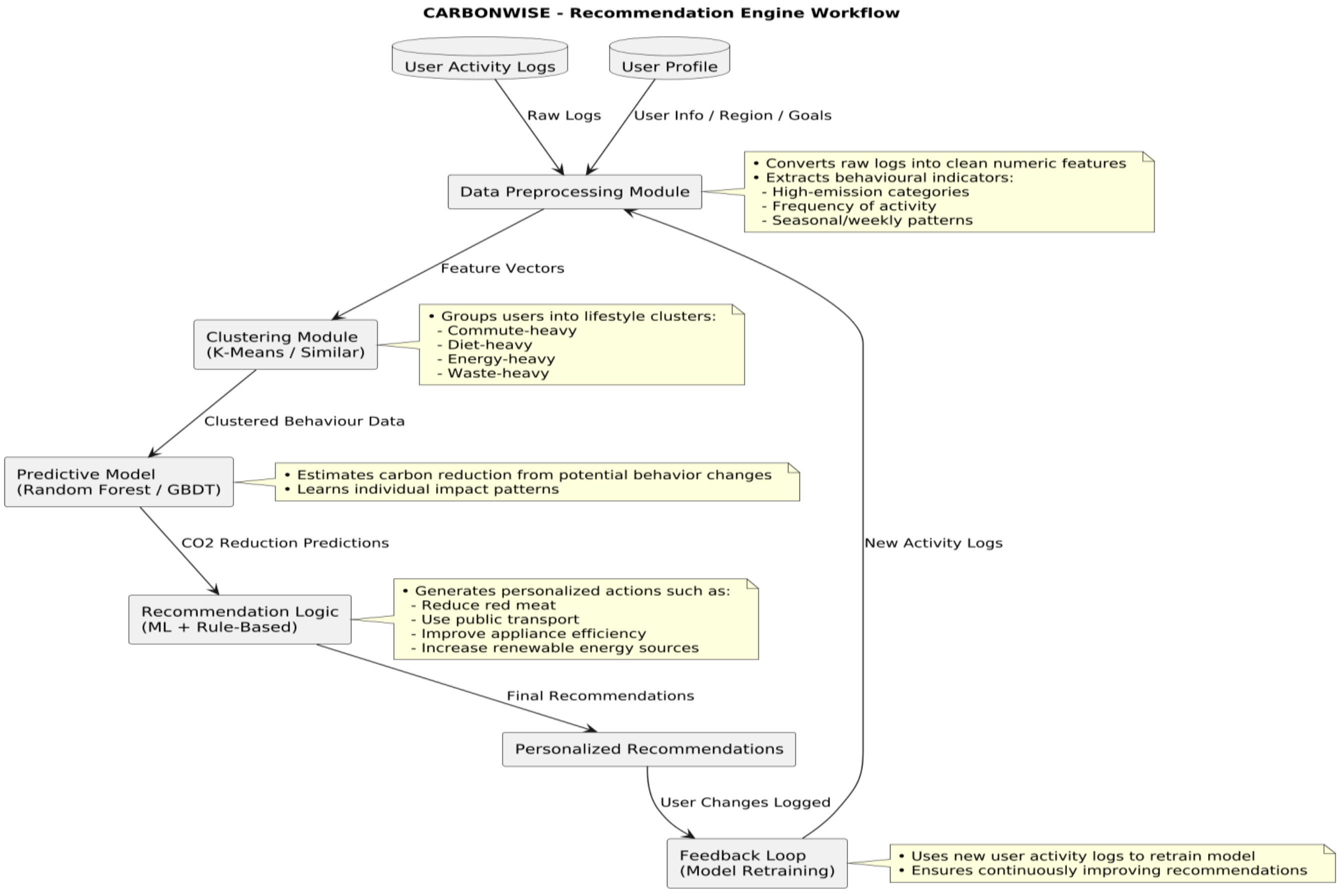

Figure 6: Recommendation Engine Workflow

The sixth figure shows the flow of the system's recommendation engine. The engine works this way: the raw user activity logs are preprocessed to remove featuresand identify emission behaviours. The users are all divided into "clusters" of lifestyle groups using K-means, and prediction models like Random Forest/Gradient Boosting. These created clusters are added to rule-based sustainability guidelines to create suggestions for the user. This is incorporated in a continuous loop, retraining the models again and again with new & updated user data to keep the recommendations adaptive.

4. Implementation

The Implementation section gives us details into the practical working of the CarbonWise system. It describes the various different components that function to achieve efficient carbon footprint analysis. This can only happen by combining the effective capabilities of the frontend, backend, database, and suggestion providing components.

4.1 System Execution Overview

Three layers, that is, the UI layer, logic layer, and data storage layer form the skeleton of the CarbonWise system. At the time of launching, the back-end configurations are set up, creates database connections, and begins operating according to the users' requirements. The system operates in an iterative manner by:

• Authenticating user sessions and Logging process

• Accurate records and saving of users' activities

• Calculating users' carbon footprints emissions

• Statistics of the data collected

• Presenting recommendations to the user

All operations in the system are carried out through asynchronous messaging.

4.2 Backend and Data Flow

The backend design of CarbonWise consists of a modular approach, providing effective information processing, storage, and communication between the components.

- Application Layer: The backend is comprised of several different modules dealing with tasks of authentication, management of activities, goals, statistics, and calculations. Requests from the frontend are validated and sent to the proper module depending on their nature.

- Storage of Data: All information about users and their activities, emissions, goals, performance, and other relevant data is stored in a database in an organized manner. Every single entry in the database has its corresponding user ID, allowing for individual data access and storage.

- Processing of Requests and Error Handling: The requests received by the system are properly validated and parsed in order to be handled effectively and securely. Moreover, the system uses built-in methods of error handling in order to cope with possible failures of the system.

4.3 Insights & Intelligence Layer

It integrates an intelligent insights layer that offers recommendations to users by analyzing their emissions and behavior patterns.

Insight Generation Based on AI: Analyze the behavior of users and emission patterns to gain insight into the key areas of their emissions and behaviors for the purpose of giving recommendations.
Output from the process includes:
• Emission reports and trends analysis
• Detection of high-impact behaviors
• Suggestions for carbon footprint reduction
• Feedback to motivate users

Data Processing Using Analytics: The user's collected data is organized to identify behavioural patterns and trends of the user's activity. This helps in offering recommendations to users.

Key analytical insights include:
• Analysis of emission patterns category wise
• Analysis of activity patterns

4.4 Frontend and User Interaction

The frontend interface design of CarbonWise is supposed to be a one-page web application that enables the user to experience a responsive and interactive interface.

The user is able to perform the following tasks:

• Secure login or registration

• Enter the details of his/her activities done daily

• View statistics about his/her emissions

• Define personal sustainable goals

4.5 System Modules And Functional Responsibilities

The CarbonWise system is made up of many functional components that are tasked with different functions which contribute to the ability of the system to track, analyze, and engage with the user.

Authentication Module: This module guarantees security in terms of user access through proper management of login details and sessions.

Activity Management Module: It guarantees the management of the creation, modification, and deletion of user activities in different categories for effective analysis of emissions.

Gamification Module: Gamification is used in this application to ensure that the user is engaged, hence encouraging them to always make environmentally friendly decisions.

Recommendation & Insights Module: It creates personalized suggestions for different activities and emission tendencies of the user through intelligent analysis and decision-making.

4.6 System Integration

Integration of all these details is done through the proper communication process. The communication between the frontend and backend happens through APIs, while that between the backend and the database happens to store and retrieve information.

This includes:

• Proper data transfer
• Scalability and modularity
• Extensibility and maintainability

5. Testing and Results

The current session now discusses the detailed testing process that we conducted to confirm the working of all CarbonWise features. This incorporates any general user creating an account, logging into the created account, calculating activity emission calculator, watching the dashboard work accordingly, and finally testing the recommendation modules. Along with each singular module, we also conducted tests that verified how well the various modules functioned together in order to test the overall efficiency of the system. The following are the procedures we followed:

- Functionality Test – To check whether the individual modules perform their functions, including user authentication, logging of activities, calculation of emission levels, updating of dashboards, and creating recommendations.
- Data Validation Test – To verify if the calculations made are correct by using emission factors for various kinds of activities.
- User Interaction Test – To figure out the user’s ease of using the dashboard
- Integration Test – To ensure effective working of the front end, back end, databases, and the recommendation engine.
- Performance Test – To test the speed of the operation of the system.

5.1 Activity Logging Interface

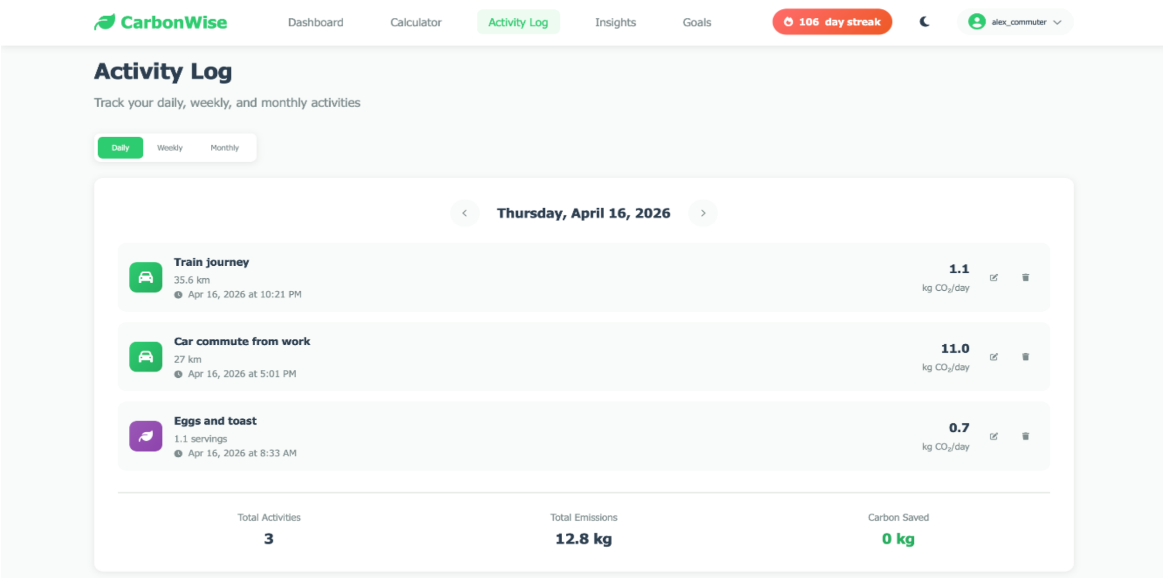

Figure 7: Activity Login Interface of CarbonWise

The seventh figure, therefore, shows an example of a user named ‘Alex’ where the user logs his daily activities in various different categories, like travel (train journey), energy usage(electricity), food consumption (eggs and toast), etc. We observed during testing that all entries efficiently, and found no errors.

5.2 Emission Calculation Output

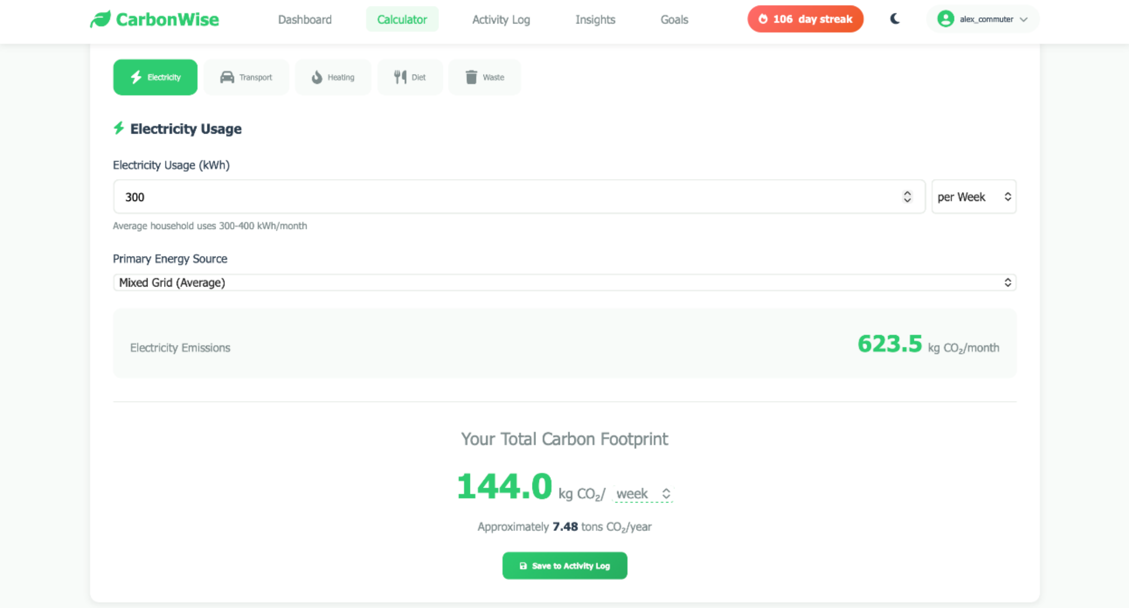

Figure 8: Emission Calculation Output of CarbonWise

The eighth figure clarifies that the system can accurately calculate carbon footprint emissions based on information input by the user. The calculated values are directly correlated with the expected carbon footprint emissions.

5.3 Dashboard Visualization

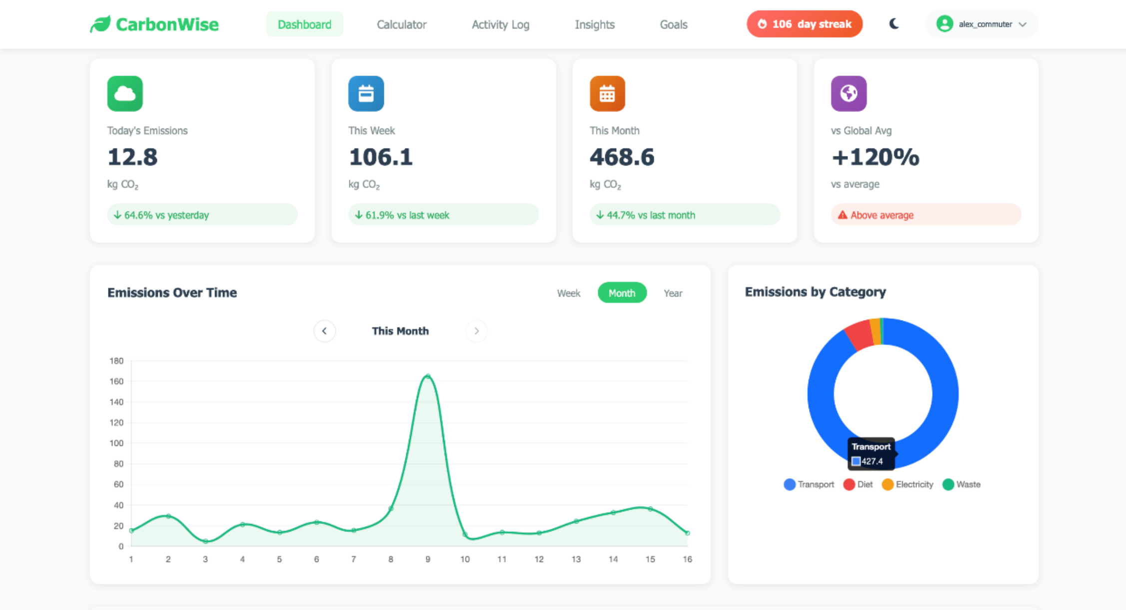

Figure 9: Dashboard Visualization of CarbonWise

The ninth figure presents the dashboard which shows the various regions of total emissions, emission that particular week, emissions in the particular moth, the user's avg vs global avg, as well as visualizations of estimations over time and emissions by category. We tested if the information was actually presented properly through graphs and charts.

5.4 Trend Analysis & Insights

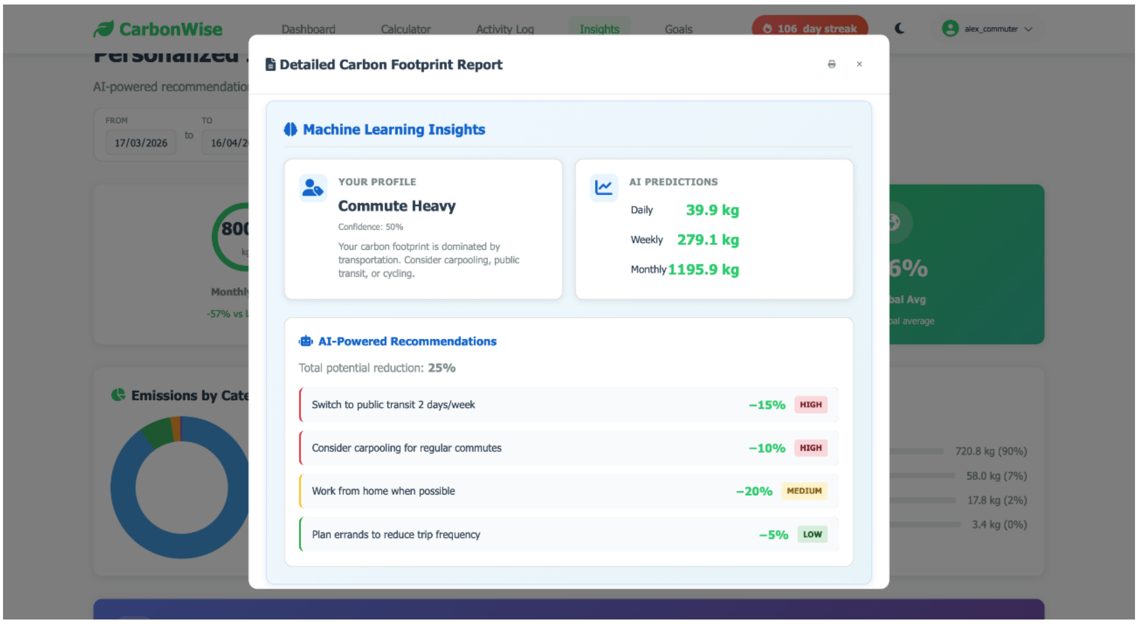

Figure 10: Trend Analysis and Insights of CarbonWise

The tenth figure shows the system's ability in analysing user data, and providing specified insights via Machine Learning like identifying patterns like high emission groups, and rising trends within them. Helps the users in understanding deeply how their behaviour effects their carbon footprint.

5.5 Personalized Recommendation

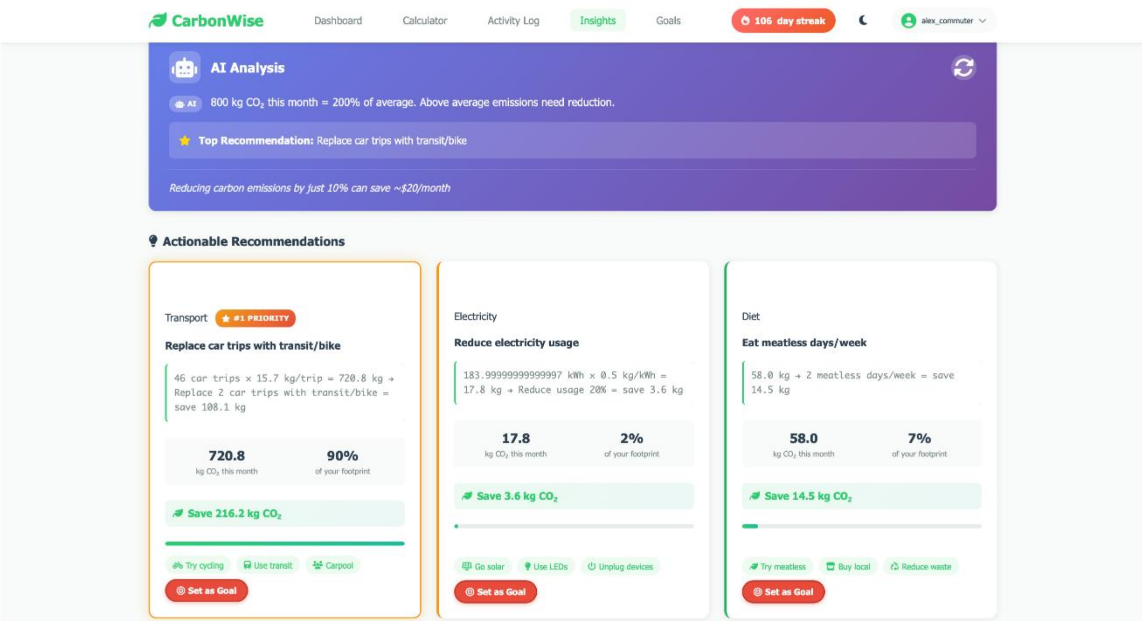

Figure 11: Personalized Recommendation of CarbonWise

Figure 11 illustrates the recommendation model. The recommendation module creates recommendations from the user activity pattern. In the testing process, the system was able to give appropriate recommendations, such as decreasing the use of private vehicles or conserving resources.

5.6 Goal Tracking and Progress Monitoring

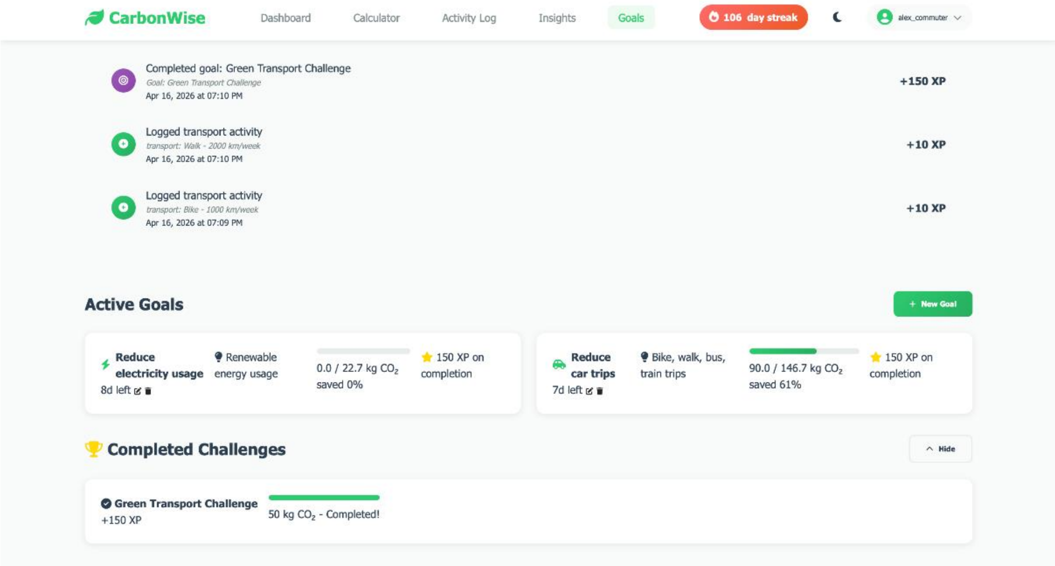

Figure 12: Goal Tracking and Progress Monitoring of CarbonWise

As shown in Figure 12, it is clear that the method employed by the users in setting up the targets for decreasing emissions and monitoring their progress through visual aids like the progress bar and percentage completion was achieved successfully. It was observed during the test that the visual aids updated themselves accurately upon entering new activity data.

5.7 Gamification Features

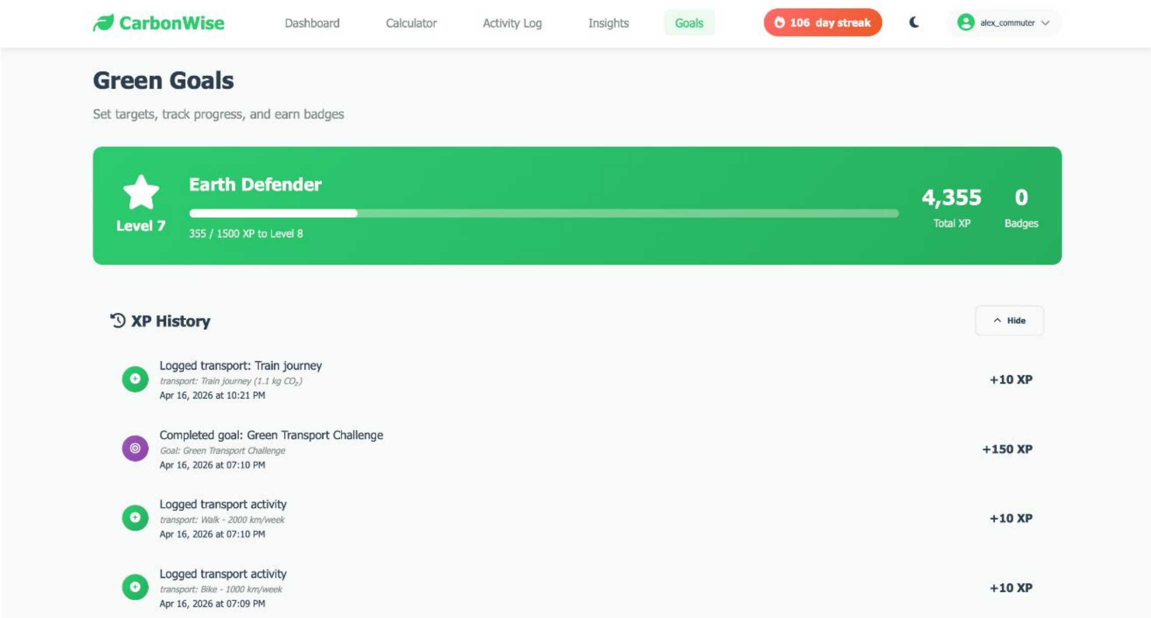

Figure 13: Gamification Features of CarbonWise

As shown in Figure 13, the effectiveness of gamification elements such as badges, streaks, and milestones was verified for their proper functioning in the system. They have been checked to function efficiently in response to the actions performed by the user and his/her achievements. From the results obtained from the verification process, it can be concluded that these gamification elements helped to improve the user's engagement on the website.

6. Conclusion and Scope for Future

6.1 Conclusion

On the whole, CarbonWise was built to be a stack-based application that could help resolve the challenges of measuring and reducing personal carbon footprint. Specifically, with the inclusion of activity tracking, calculation of emissions, visualization of data, and provision of recommendations, CarbonWise enables users to control their impact and change their lifestyles.

It is evident that the application demonstrates how various activities in everyday life (such as transportation, use of electricity, diet, among others) are transformed into carbon dioxide equivalents due to specific emission factors. The visualization of calculated data and the opportunity to analyze trends provide opportunities for gaining a deeper idea of users' carbon footprints.

The personalized recommendations provided in the application, based on activity analysis and identification of the high-carbon consumption activities, prove to be an effective feature of the application. Furthermore, the application has gamification options such as badges and streaks, as well as goal setting and progress tracking.

Based on the results of the various tests, the system functions very efficiently because it is able to calculate users' accurate emission values, as well as updating in dashboard and visualizations in real time. The correlated working of backend, frontend, databases and ML modules is perfect. All in all, the system achieves the core objective of the website.

6.2 Future Scope

The system works as it should, but there are some ways we believe it could be improved:

Better data collection, integration and automation: Right now, users have to type in information about their activities by manual. In the future, it might be possible to connect with other API's and Iot devices, like smart meters, health tracking apps, or travel apps, which can automatically read user data.

The enhancements which can be made to the recommendation system can be made by integrating more sophisticated AI algorithms and by merging rule-based AI with LLMs to gain deeper insights into user behaviour and suggest sustainable practices accordingly

Another future enhancement can be the building of a mobile application. The users' phones can have the mobile app that helps them track their physical activity. With this app, users will be able to get suggestions immediately, even notifications about how their efforts can be more towards sustainability.

Finally, another improvement can be to provide a community/social features. Like being able to compare users' sustainability efforts within their friend groups/ families. This would also increase user engagement with the CarbonWise website.

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