Development of Smart Real-time Monitoring System for the Determination of Household's Carbon Footprint Using Interactive Energy Audits

Hameedat Bashir[1]; James Garba Ambafi[1]; Kufre Esenowo Jack[2]

[1]Department of Electrical and Electronics Engineering, School of Electrical Engineering and Technology, Federal University of Technology Minna, Niger State, Nigeria.

[2]Department of Mechatronics Engineering, School of Electrical Engineering and Technology, Federal University of Technology Minna, Niger State, Nigeria.

bhameedah0182@gmail.com, ambafi@futminna.edu.ng, kufre@futminna.edu.ng

*Corresponding Author: James Garba Ambafi, ambafi@futminna.edu.ng, +234 805 741 5703

Received: xx.xx.xxxx Accepted:xx.xx.xxxx

Abstract--The digital transformation ushering in Industry 4.0 has heightened energy consumption and carbon emissions, necessitating energy-efficient methods. This thesis tackles carbon reduction and energy efficiency through a smart real-time monitoring system for household carbon footprints using Interactive Energy Audits (IEAs), in alignment with Sustainable Development Goal 12 (SDG 12). The system aims to empower households to monitor and control energy usage, fostering awareness and behavior change towards a sustainable future. The research focuses on developing a user-friendly IEA interface for real-time energy consumption input and tracking, a robust backend system for data collection, linear regression machine learning algorithms for personalized recommendations, and cloud infrastructure for data storage and analysis. Despite advancements in energy monitoring, integrating these components with real-time data analytics and machine learning remains underexplored. The methodology includes designing an intuitive user interface, developing a robust backend for real-time data analysis, implementing machine learning for tailored recommendations, and utilizing cloud storage for data. Results demonstrate that the proposed system can reduce household carbon emissions by up to 98%, as determined by the linear regression algorithm. The model provided insights into the impact of energy consumption on the carbon footprint, enabling users to make informed, sustainable decisions and save costs. Recommendations include refining machine learning models for greater accuracy, expanding user education programs, and broader system deployment to achieve significant carbon footprint reduction. This research advances the goal of responsible consumption and production by promoting household energy efficiency and environmental awareness.

Keywords: *Carbon, Emission, Energy Audits, Linear regression, Real-time, Monitoring System*

I. INTRODUCTION

Globally, the human race is undergoing a huge digital transformation, plunging the world into an Industry 4.0 era, representing a new technological evolution. This evolution is in response to population growth and fast industrialisation, increasing energy demand and supply, leading to the depletion of huge quantities of energy reserves. However, given these changes, there is a growing concern over the effect of digitisation and data processing on contributing to an increase in carbon footprint. Carbon emissions have been a cause for sustainability concern due to their environmental impact. Today, carbon emission is a major contributor to global warming. The US greenhouse gas emission highlights carbon as a leading component, accounting for about 79% of the greenhouse gases in the atmosphere [1]. Generally, lives are being impacted negatively by global warming, such as the rapid rise in sea level and extreme temperatures. Studies have shown that beaches and islands will be submerged completely in the next thirty years if poorly managed carbon emission rates [2].

Carbon footprint is the total amount of greenhouse gases, especially carbon dioxide (CO_2) and other carbon compounds, emitted directly and/or indirectly by an individual, organisation, event, or product through its lifecycle. The greenhouse gases contribute to the greenhouse effect and global warming by trapping heat in the atmosphere. The growing demand for energy usage impacts the rate of emission of carbon. The combustion of energy from power plants, industries, transport systems, commercial centres, households, and other sectors contributes to carbon emission into the atmosphere in varying quantities. Energy-saving methods are deployed to curb the effects of these emissions, which necessitates using energy wisely and efficiently for beneficial usage. Energy savings serve as a means of energy usage control, cost saving, increase in environmental values and improvement in comfort [3] .

Energy management is one such method implemented in energy control. The Steps required in energy management are monitoring, controlling, energy conservation and evaluating energy usage in household buildings or companies. Energy management is an automated system that collects data from monitoring and measurement devices from the field, processes it, and makes it available visually for easy understanding by users. Adequate care must be taken in determining the monitoring points to enable proper measurements on the electricity network. A data acquisition system is developed, where monitoring devices are installed throughout the network to enable the transfer of energy usage data at each monitoring or measurement point to the control centre via a communication system [4].

Various research has been carried out on monitoring energy consumption using different methods. These methods are advancing technologically, from direct or conventional monitoring to cable or wireless technology. A well-developed method that can be used to monitor electricity consumption is energy audit. Energy auditing is useful in helping individuals or groups identify sections where energy usage in the system can be reduced without affecting its overall output or performance in the system. It is important to identify these areas to reduce carbon footprint and improve the saving cost of energy in households. The system observes energy consumption in the household and develops an efficient method for optimising energy usage by increasing efficiency. Reference [5] carried out a comprehensive study of efficient and inefficient appliances used in households in Nigeria. About 48% energy saving was obtained by replacing old devices with new ones. The carbon emissions and greenhouse gasses were greatly reduced after analysis using building energy audit data.

This research aims to develop a smart real-time monitoring system for estimating household carbon footprints using interactive energy audits. To achieve this aim, the research will carry out a user preference survey and analysis, design and implement a user-friendly Interactive Energy Audit (IEA) interface with reliable cloud infrastructure for storing and analyzing user data, develop a robust backend system capable of integrating with smart devices and sensors to collect real-time data on household energy usage and implement machine learning algorithms to analyze the collected data and provide personalized recommendations for energy-efficient practices.

II. REVIEWED LITERATURE

A. *Concept of carbon footprint*

Ecological footprints describe the number of global hectares of ecologically productive land and sea needed to support a specific human population. This idea states that a person's carbon footprint is the amount of land needed to absorb all the CO_2 that humans have ever produced. The concept of carbon footprint became widely used over time as the global warming issue gained importance on the international environmental agenda, albeit in a modified form [6]. Although it goes by a different name, "life cycle impact category indicator global warming potential," the idea of carbon footprint has existed for a few decades [7].

Despite the current focus on carbon footprint, little research provides data on global hectares, according to [8]. Additionally, it is noted that there is a dearth of scientific literature on the topic and that private groups and enterprises have conducted the majority of the investigations primarily out of business acumen rather than environmental concern [9].

The terms embodied carbon, carbon content, embedded carbon, carbon flows, virtual carbon, Green House Gases (GHG) footprint, and climate footprint" are also occasionally used interchangeably with carbon footprint in the literature that is currently available [10]. A new phrase called climate footprint was developed as a complete GHG indicator, meaning that if all GHGs coming from within the border are quantified, then that is the indicator.

The choices made for embodied and direct emissions are not consistent. Emissions produced immediately while a process is underway are called direct emissions. One instance of a direct emission is CO_2 emitted during burning in an industrial boiler that runs on gasoline. Nevertheless, no direct emissions will be seen in an electrically heated boiler. However, the quantity of CO_2 released during the production and transmission of the electrical units utilized in the boiler is referred to as embodied or indirect emission if the electricity was produced in a thermal power plant.

Since accounting for every potential emission becomes complicated, most studies only provide first-order indirect or direct emissions, as [11] studied. The gases used and the boundaries defined for the carbon footprint calculations by various organizations vary greatly due to the lack of consistency in selecting the characteristic attributes of the carbon footprint [12].

The quantification of greenhouse gas emissions from an activity, known as the carbon footprint, aids in controlling emissions and assessing mitigation strategies [13]. After the emissions have been measured, the most significant sources of emissions can be located, and the areas where emissions can be reduced, and efficiency can be increased can be given priority. Cost savings and environmental efficiencies are made possible by this. Most businesses and nearly all individual carbon foot printing initiatives have been noted to focus on lowering emissions or offsetting footprints by purchasing carbon credits or other control measures. As a result, there is a global rush to determine carbon footprints and reduce emissions to gain a competitive edge [6].

A handy method to evaluate the contributions of different countries, cities, and sectors to global warming is to look at the country-wise per capita carbon footprint provided by [14]. Wealthy nations leave the largest environmental footprints, whilst developing nations leave far smaller ones. Research has been published on the quantitative carbon footprint impact of natural and semi-natural systems as studied by [15].

B. *Energy Audit*

In their paper, [16] used the audit of a fume exhaust system blower used in a cold rolling mill to illustrate the need for different energy audit methodologies. The fume exhaust blower was equipped with a 50 HP, 415 V, three-phase AC induction motor rated at 1460 rpm. The blower fan in the prior setup always ran at full speed and a constant speed regardless of whether fumes were produced because a belt pulley and a Star Delta starter for the motor powered it. Noting their discoveries, the author offered an improved method of utilizing the energy flow. The current technology optimizes power consumption while the mill is idling thanks to an AC electronic speed variable drive and software tailored to the drive's functioning. Following installation, the new system features a smooth start that prolongs the motor's life and saves energy because it adjusts for variations in speed and voltage while the mill is idle. In their work, they have talked about the potential for energy savings, the necessity of putting energy-saving measures into practice, and prospective ways to conserve energy by using it properly. Energy-saving computations were performed to determine how much energy may be saved by swapping out appliances for ones with more energy-efficient parts. The investment cost and capital cost recovery time (payback period) were also computed for every recommendation. Other recommendations in this report include replacing Cathode-ray Tube (CRT) monitors with

Liquid Crystal Display (LCD) monitors, switching from geysers to solar water heating systems, and using motion sensors in restrooms and hallways to turn off lights automatically when no activity is detected. In their study on energy auditing of an educational institute [17], emphasizes the significance of auditing by considering traditional lighting load, replacing it with energy-efficient bulbs, and comparing the results.

In 2015, [18] performed an energy audit on Aurangabad's "Kohler Power India" industry. Founded in 1873, The Kohler Company is a manufacturing firm headquartered in Kohler, Wisconsin. Despite being most recognized for its plumbing goods, the company also produces generators, engines, furniture, tile, and cabinets. This report details the preliminary energy audit at the Kohler facility in Aurangabad, where energy-saving suggestions were noted.

All these standards concur that building energy audits are essential for determining how efficiently energy is used in buildings and serve as the foundation for any decisions made to improve energy management. While some of the monthly provide advice and help for conducting audits, others outline strict requirements that must be fulfilled for a user to claim compliance with the standard. The standards offer a wide range of criteria for energy audits, contingent on the degree of specificity and human resources needed to carry them out. The following sections critically evaluate the research efforts and applications for energy audits and assessments for existing buildings, emphasizing two crucial areas: the performance criteria for the evaluation and the technique employed for energy use.

C. *Machine Learning Method for Carbon Emission*

Setting regulatory requirements and promoting self-regulation requires understanding GHG emissions and their downstream effects [19]. These estimates are specifically used to establish targets for reducing carbon emissions and establishing carbon pricing for taxes or emissions trading schemes. Many studies have looked at the accounting and modelling of carbon emissions at various granularities: at the international level [20], using national estimates focusing on a specific industrial sector, such as information and communication technologies, which was modelled by [21]; or even focusing on a specific application, such as bitcoin mining, which was modeled by [22].

Applications such as bitcoin mining have previously been the subject of some studies that have specifically analyzed the carbon implications by [23]. Prioritizing emissions mitigation techniques requires these application-specific initiatives since policy choices may concentrate on inefficient regulation without knowing the anticipated effects. However, modelling every facet of an application's usage can be challenging due to the underlying data's high levels of variability and endogeneity. As an illustration, a study by [24] claimed that "bitcoin emissions alone could push global warming above 2°C. However, [25], and others questioned the underlying modelling assumptions that produced such big estimations of carbon emissions. This demonstrates how important it is for these models to offer precise data to be applied to well-informed decision-making. We wish to learn more about how machine learning in academia and business affects climate change because ML models are becoming increasingly computationally demanding [26]. Nevertheless, because of a current dearth of reporting and accounting, assessing the overall climate change implications of Machine Learning research and applications would necessitate making numerous assumptions. Our goal is to support and promote systematic reporting systems instead so that future field-wide estimates can be undertaken accurately. The effects of machine learning research on the climate are the subject of some recent studies. Reference [27] examines anticipated power consumption to highlight big NLP models' carbon and energy consequences.

Similar recommendations were made by [28], who proposed floating point operations (FPOs) as a guiding efficiency parameter. A website for calculating carbon emissions based on GPU kind, experiment duration, and cloud provider was just made available by [29]. Though largely concentrating on emissions from conference travel, earlier studies have also looked at the carbon implications of research in various sectors [19].

III. METHODOLOGY

The successful implementation of an effective smart real-time monitoring system for the determination of household carbon footprint depends on the appropriate selection of materials and methods, technologies, and algorithms. Artificial intelligence plays a pivotal role in this context, leveraging deep learning, and sensor networks to create an accurate carbon emission model. This system employs sensor-based data collection. This combination results in the creation of a carbon prediction model, facilitating real-time monitoring and data logging essential for effective household carbon emission monitoring.

A. *Materials*

The material used in this research is Google's Form, which helps analyses consumer needs and expectations for a visual and interactive interface while the interface is developed on MIT App Inventor. This is a web-based, high-level, block-based visual programming language. This allows the building of an IoT interface using visual block tools.

B. *Methods*

A survey was conducted using Google Forms to understand consumer needs, their familiarity with energy monitoring tools, and their willingness to monitor energy consumption. The form included questions about energy use, technical proficiency, monitoring patterns, tool preferences, interface preferences, challenges, and suggestions. The survey was piloted with a small group to identify and correct any issues before being distributed to a diverse group of users from different geographic locations.

i. ***User- friendly interface design***

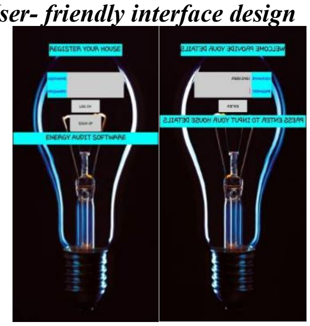

Figure 1: Interface login and device capturing

The final front-end design for the Interactive Energy Audit (IEA) interface was implemented using the MIT App Innovator, based on user preference survey results. The interface was simulated on a mobile phone to ensure compatibility and responsiveness as shown in Figure 1. Wireframes and prototypes were developed to meet the gathered requirements, and multiple feedback sessions were held to refine the interface features. Secured authentication and access control were integrated to ensure user data security, leveraging MIT App Innovator's web-based coding capabilities. Usability tests with potential users were conducted to evaluate the effectiveness and user-friendliness of the interface, identifying technical issues and areas for improvement.

The IEA interface is designed to be scalable and capable of handling increasing numbers of users and data points. It requires detailed information about household devices, including power ratings and average usage, to perform accurate audits. The interface calculates real-time energy consumption for each device, allowing users to add or remove devices easily through input fields and prompts. This flexibility ensures that the interface can adapt to changes in household energy consumption, providing up-to-date information.

Based on the energy audits conducted by the interface, the household's carbon footprint is calculated and visually represented to show greenhouse gas emissions. The interface analyzes energy consumption data to calculate total energy use and the associated carbon footprint, helping users understand their energy habits and environmental impact. The interface encourages more energy-efficient behaviours by providing users with an easy-to-understand interpretation of their carbon footprint and suggestions for reducing it through the visualisation of greenhouse gas emissions. Figure 2 shows the interface for the Real-time carbon footprint monitoring.

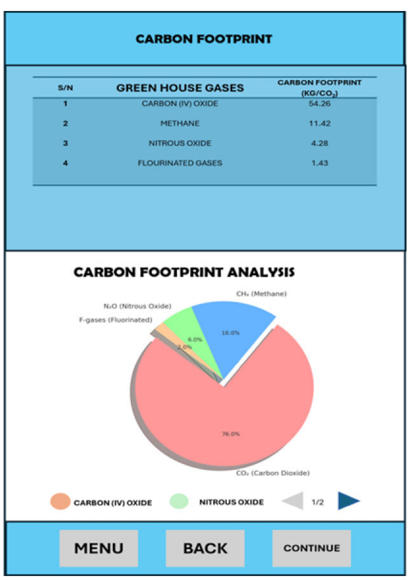

Figure 2: Real-time carbon footprint monitoring

ii. ***Backend system development.***

The interface for the energy monitoring system was developed using the MIT App Inventor, a visual development web environment that allows users to design and create mobile applications with visual code blocks. This user-friendly platform facilitates the development of interactive interfaces without requiring extensive programming knowledge. It supports both Android and iOS platforms, enhancing its availability and flexibility. The drag-and-drop feature and visual code blocks were employed to create well-tailored features for the mobile application.

The backend code development using visual code blocks followed several stages of implementation. First, a user input interface was created using text boxes and dropdown menus to enable users to sign up and input their home and device details this is shown in Figure 3. TinyDB, a built-in database feature of MIT App Inventor, was utilized for data storage and management, ensuring that users' home details are stored in an organized and accessible manner.

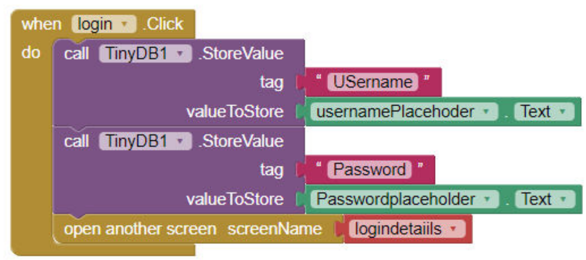

Figure 3: Building blocks for the user input interface.

For real-time monitoring and control, ON/OFF components were used to allow users to switch the state of their devices, with dynamic labels displaying the real-time state and energy consumption data of each device. These labels were linked to the TinyDB database for real-time data retrieval, this is shown in Figure 4. Mathematical calculation code blocks were employed to calculate household energy consumption and carbon footprint, with the results visually represented using the chart component of MIT App Inventor.

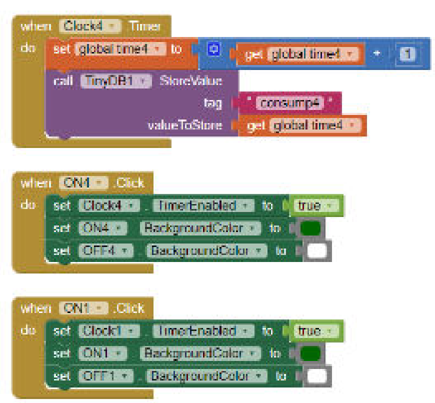

Figure 4: Visual blocks for remote control of devices.

Moreso, display components such as labels and lists were used for monitoring individual device consumption rates and usage times, presenting the data concisely and in an organized manner. The chart component was again utilized to visually represent the calculated values, showing the percentage of energy consumption of the household. This comprehensive approach provides users with a clear understanding of their energy usage and its environmental impact. Figure 5 shows the chart component utilized to represent the calculated values visually; this is to represent the percentage energy consumption of the household.

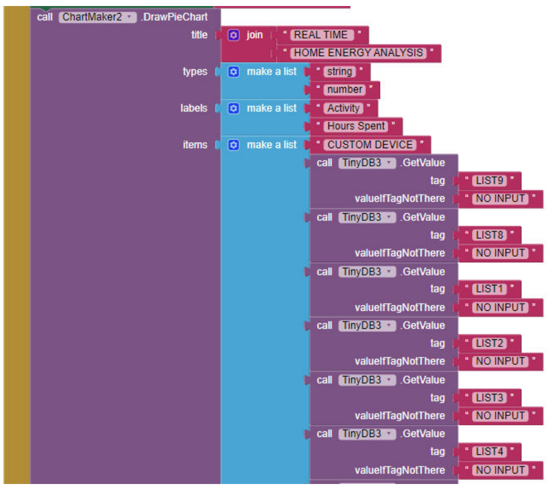

Figure 5: Chart component utilized for energy consumption.

iii. Linear regression modelling.

The interactive real-time energy audit interface was designed to collect, store, and update detailed information about the user's household and registered devices, including energy consumption, power rating, and usage hours. The interface provides real-time household carbon footprint data based on device information, stored in the MIT App Inventor's inbuilt TinyDB database. This data is organized into a structured table for machine learning analysis, focusing on energy consumption and carbon footprint.

The project employs Linear Regression due to the dataset's linearity and the model's simplicity. The model was developed using the Jupyter web-based environment. The necessary libraries for data manipulation, visualization, and machine learning tasks were imported, and the dataset was extracted from a CSV file named "user data" into a pandas' data frame. Figure 6 shows the importation of the necessary library for data manipulation, visualisation, and machine learning tasks.

```
[17]: # Importation of Libraries

import numpy as np
import pylab as pl
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


import plotly as py
import plotly.graph_objs as go

from sklearn import linear_model

import warnings
warnings.filterwarnings('ignore')
```

```
[2]: #Importation of Live data and headers
df = pd.read_csv('User_data.csv')
df.head()
```

[2]:

	Date	Avg_EG	CF_kg
0	26/02/2024	4.48	1.80096
1	1/10/2023	5.83	2.34366
2	29/10/2023	6.61	2.65722
3	28/02/2024	6.62	2.66124
4	27/01/2024	8.87	3.56574

Figure 6: Data importation using data manipulation libraries.

IV. RESULTS AND DISCUSSION

This section presents a description of results achieved from the objectives carried out. An overview of the user interface developed with its functionality and how the features were implemented and its functionality. Results from the Google Forms survey revealed average user energy consumption, technical proficiency, estimated consumption, and monitoring patterns. This study examined energy consumption diversity across demographics such as household size, location, lifestyle, and socioeconomic status. Understanding this range is crucial for developing a monitoring system that meets the needs of various households, optimizing energy usage, and reducing carbon footprints.

Users' familiarity with interactive tools was evaluated, categorizing them from beginner to expert levels. This categorization helps tailor the user interface and experience of the smart real-time monitoring system to different technical skills, showing consumers' monitoring patterns and identifying areas for improvement. The survey also highlighted the various tools consumers use for energy monitoring, from traditional methods to newer technologies, providing insights for integrating an efficient smart real-time monitoring system as shown in Figure 7.

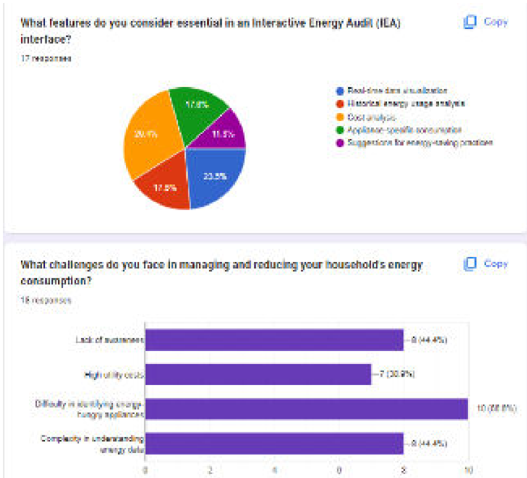

Figure 7: Survey results for consumer interface feature preference.

The survey identified motivating factors for consumers to monitor their energy consumption, crucial for crafting effective features and suggestions. Challenges such as lack of awareness, high utility costs, and difficulty understanding energy data were highlighted. Understanding these hurdles helps in developing strategies that align with user preferences, promoting sustainable energy practices through targeted recommendations and enhancing user readiness to adopt energy-saving measures.

An initial audit of the household devices is carried out to understand the household estimated energy usage and to form a baseline in energy efficiency methods. Figure 8 shows initial audit for a user and the control interface for the control of each device. User can remotely and actively determine which device to be in use. The interface then records usage time and calculates the household energy consumption in real time.

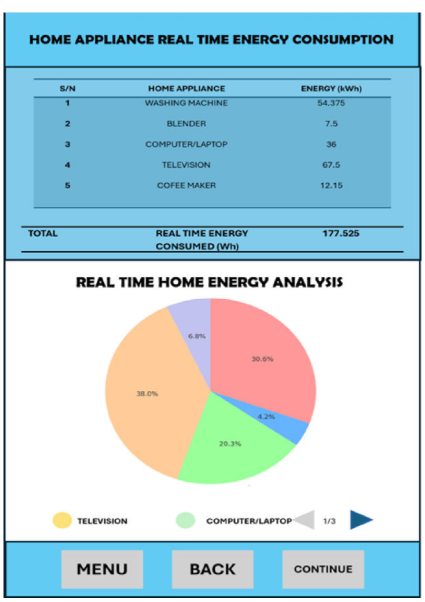

Figure 8. Household audit and control

Based on the audit carried out by the interface, the household's carbon footprint is calculated and represented visually to show the percentage of greenhouse gas emissions.

Data from device usage patterns is used to estimate the household carbon footprint associated with energy consumption. The interface analyses this data to calculate total energy consumed and the corresponding carbon footprint, enabling users to understand their energy usage habits and environmental impact. Users can identify ways to reduce their carbon footprint through this analysis. The interface visually represents greenhouse gas emissions on a chart for easy interpretation.

A linear regression machine learning model was implemented to analyse, visualize, model, and evaluate the relationship between energy consumption and carbon footprint. Using data from MIT TinyDB, the model predicts the household carbon footprint based on energy consumption. Evaluation metrics indicate how accurately the model predicts the target carbon footprint, providing valuable insights.

The Model checks for the shape of the dataset in a bid to understand the number of rows and columns and the labels of the columns. It then describes the dataset statistics while checking for missing values and duplicates in the rows of the dataset. It plots a histogram and a pair plot to visualize the distribution and relationship between the input variables as shown in Figure 9 and Figure 10.

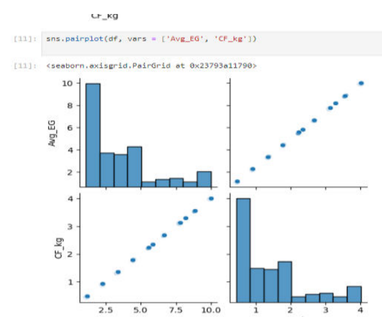

Figure 9: Dataset representation as a pair plot

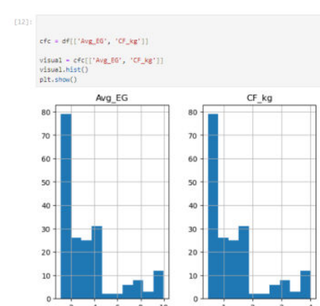

Figure 10: Histogram representation of the dataset

The data is split into a training set representing 80% of the data and a testing set representing 20% of the data. It then applies the linear regression model to the training data to model the relationship between average energy consumption (Avg_Eg) and carbon footprint (CF_kg). The coefficients and intercept of the linear regression model are calculated, and a visualisation of the regression model is plotted on a scatter plot of the training data as shown in Figure 11.

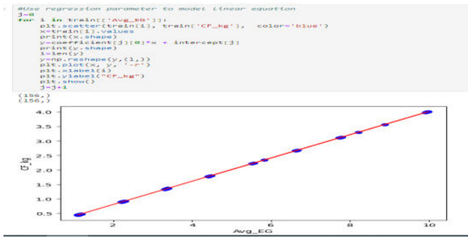

Figure 11: Scatter plot visualisation of the Linear regression model.

The Mean Absolute Error (MAE) measures the average absolute difference between predicted and actual values, with a lower MAE indicating more accurate predictions. Here, a MAE of 0.00 means the predictions perfectly match the actual values. The Mean Squared Error (MSE) measures the average squared differences between predicted and actual values, penalizing larger errors more heavily. An MSE of 0.00 also indicates a perfect match. The R2-score, or coefficient of determination, measures how well the independent variable (energy consumption) predicts the dependent variable (carbon footprint), with a value of 1 indicating a perfect fit. The values of 0 for MAE and MSE and 1 for the R2 score suggest the model perfectly predicts the carbon footprint based on energy consumption.

V CONCLUSION

The development of a smart real-time monitoring system for determining household carbon footprints using interactive energy audits (IEAS) was guided by objectives focused on creating a user-centric and efficient tool. Employing User-Centred Design (UCD) principles, the IEAS interface was tailored to user needs, allowing for easy input of home and device details, real-time device control, and energy usage monitoring. Standardized data formats and protocols enabled real-time energy consumption data collection, providing users with insights to optimize their energy use and reduce their carbon footprint.

Using visual code blocks in the MIT App Inventor, the backend code facilitated the implementation of a linear regression machine learning model. This model analyzed the relationship between energy consumption and carbon footprint, predicting the carbon footprint based on household energy use. The insights from the model helped users make sustainable decisions to reduce their environmental impact and save costs.

ACKNOWLEDGEMENT

I am deeply thankful for the guidance and support provided by my supervisors throughout this research endeavour. Their invaluable insights and expertise significantly contributed to the success of this model.

REFERENCES

[1] Sharma, P., & Dash, B. (2022). The Digital Carbon Footprint: Threat to an Environmentally Sustainable Future. *International Journal of Computer Science and Information Technology*, 14(03), 19–29. https://doi.org/10.5121/ijcsit.2022.14302

[2] Stolz, S., & Jungblut, S. (2019). Our Digital Carbon Footprint: What's the Environmental Impact of the Online World? – Digital for Good | RESET.ORG. Our Digital Carbon Footprint: What's the Environmental Impact of the Online World?

[3] Rasmussen, J. (2017). The additional benefits of energy efficiency investments—a systematic literature review and a framework for categorisation. Energy Efficiency, 10(6), 1401–1418. https://doi.org/10.1007/s12053-017-9528-1

[4] Bagus, I., Purwania, G., Kumara, I. N. S., & Sudarma, M. (2020). Application of IoT-Based System for Monitoring Energy Consumption. *International Journal of Engineering and Emerging Technology*, 5(2), 81–93.

[5] Darshan, A., Girdhar, N., Bhojwani, R., Rastogi, K., Angalaeswari, S., Natrayan, L., & Paramasivam, P. (2022). Energy Audit of a Residential Building to Reduce Energy Cost and Carbon Footprint for Sustainable Development with Renewable Energy Sources. Advances in Civil Engineering, 2022. https://doi.org/10.1155/2022/4400874

[6] Torrubia, J., Valero, A., & Valero, A. (2023). Resources , Conservation & Recycling Energy and carbon footprint of metals through physical allocation . Implications for energy transition. Resources, Conservation & Recycling, 199(October), 107281. https://doi.org/10.1016/j.resconrec.2023.107281

[7] Schleich, J., Dütschke, E., Kanberger, E., & Ziegler, A. (2024). On the relationship between individual carbon literacy and carbon footprint components. Ecological Economics, 218(December 2023), 108100. https://doi.org/10.1016/j.ecolecon.2023.108100

[8] Hoffmann, S., Lasarov, W., Reimers, H., & Trabandt, M. (2024). Carbon footprint tracking apps . Does feedback help reduce carbon emissions ? Journal of Cleaner Production, 434(December 2023), 139981. https://doi.org/10.1016/j.jclepro.2023.139981

[9] Bowler, A. L., Rodgers, S., Meng, F., Mckechnie, J., Cook, D. J., & Watson, N. J. (2024). Development of an open-source carbon footprint calculator of the UK craft brewing value chain. *Journal of Cleaner Production*, 435(May 2023), 140181. https://doi.org/10.1016/j.jclepro.2023.140181

[10] Kartika, W., Hsieh, C., & Yang, S. (2024). Social influence and climate change issues affecting consumer behavioral intention toward carbon footprint label : A study of Taiwanese consumers. Journal of Cleaner Production, 444(September 2023), 141092. https://doi.org/10.1016/j.jclepro.2024.141092

[11] Chuter, R. (2023). IPEM-Translation Could building more satellite centres reduce the carbon footprint of external beam radiotherapy ? IPEM-Translation, 6–8(December), 100021. https://doi.org/10.1016/j.ipemt.2023.100021

[12] Deveci, M., Gokasar, I., Pamucar, D., Alaa, A., & Wei, W. (2024). Advantage prioritization of digital carbon footprint awareness in optimized urban mobility using fuzzy Aczel Alsina based decision making. *Applied Soft Computing*, *151*(December 2023), 111136. https://doi.org/10.1016/j.asoc.2023.111136

[13] Merkle, E. M., Bamberg, F., & Vosshenrich, J. (2023). The Impact of Modern Imaging Techniques on Carbon Footprints : Relevance and Outlook. *European Urology Focus*, *9*(6), 891–893. https://doi.org/10.1016/j.euf.2023.09.009

[14] Kumar, H. (2018). *Carbon Footprint of Roads : A Literature Review*. *6*(11), 4–6.

[15] Schleich, J., & Alsheimer, S. (2024). *The relationship between willingness to pay and carbon footprint knowledge : Are individuals willing to pay more to offset their carbon footprint if they learn about its size and distance to the 1 . 5 ◦ C target ?* *219*(September 2023).

[16] Ademola Olatunji Jimoh, James Demshakwa-Demenongo, & Onazi Ochepa. (2023). A Comparative Analysis of Carbon Footprints of Selected Office Buildings in Jos, Nigeria. *Journal of Energy Technologies and Policy*. https://doi.org/10.7176/jetp/13-2-03

[17] Gillespie, J., Cama-moncunill, X., Ward, S., Condell, J., Ramanathan, R., & Murphy, F. (2023). *A Systematic Review of Real-Time Monitoring Technologies and Its Potential Application to Reduce Food Loss and Waste : Key Elements of Food Supply Chains and IoT Technologies*.

[18] Spudys, P., Jurelionis, A., & Fokaides, P. (2023). Conducting smart energy audits of buildings with the use of building

information modelling. *Energy and Buildings*, *285*, 112884. https://doi.org/https://doi.org/10.1016/j.enbuild.2023.112884

[19] Schwarm, K. K., & Spearrin, R. M. (2023). Real-time FPGA-based laser absorption spectroscopy using on-chip machine learning for 10 kHz intra-cycle emissions sensing towards adaptive reciprocating engines. *Applications in Energy and Combustion Science*, *16*(November), 100231. https://doi.org/10.1016/j.jaecs.2023.100231

[20] Zheng, L., Mueller, M., Luo, C., & Yan, X. (2024). Predicting whole-life carbon emissions for buildings using different machine learning algorithms : A case study on typical residential properties in Cornwall , UK. Applied Energy, 357(December 2023), 122472. https://doi.org/10.1016/j.apenergy.2023.122472

[21] Lun, P., Savadkoohi, M., Arbayani, M., Niemi, J. V, Timonen, H., Pandolfi, M., Querol, X., Hussein, T., & Pet, T. (2024). *Constructing transferable and interpretable machine learning models for black carbon concentrations*. *184*(November 2023). https://doi.org/10.1016/j.envint.2024.108449

[22] Kang, J., Zhang, B., & Dang, A. (2024). International Journal of Applied Earth Observation and Geoinformation A novel geospatial machine learning approach to quantify non-linear effects of land use / land cover change (LULCC) on carbon dynamics. *International Journal of Applied Earth Observation and Geoinformation*, *128*(November 2023), 103712. https://doi.org/10.1016/j.jag.2024.103712

[23] Singh, R. K., Biradar, C. M., Behera, M. D., Prakash, A. J., Das, P., Mohanta, M. R., Krishna, G., Dogra, A., Dhyani, S. K., & Rizvi, J. (2024). Ecological Informatics Optimising carbon fixation through agro-forestry : Estimation of aboveground biomass using multi-sensor data synergy and machine learning. *Ecological Informatics*, *79*(December 2023), 102408. https://doi.org/10.1016/j.ecoinf.2023.102408

[24] Sarwar, S., Aziz, G., & Kumar, A. (2023). Geoscience Frontiers Implication of machine learning techniques to forecast the electricity price and carbon emission : Evidence from a hot region. *Geoscience Frontiers*, *xxxx*, 101647. https://doi.org/10.1016/j.gsf.2023.101647

[25] Xu, M., Sun, C., Zhan, Y., & Liu, Y. (2023). Geoscience Frontiers Impact and prediction of pollutant on mangrove and carbon stocks : A machine learning study based on urban remote sensing data. *Geoscience Frontiers*, *xxxx*, 101665. https://doi.org/10.1016/j.gsf.2023.101665

[26] Yedilkhan, D., & Smakova, S. (2024). ScienceDirect ScienceDirect Machine Learning Approaches for Smart Home Device Recognition Machine Learning Approaches for Smart Home Device Recognition from Network Traffic from Network Traffic. *Procedia Computer Science*, *231*, 709–714. https://doi.org/10.1016/j.procs.2023.12.157

[27] Wang, H., Wang, Y., Wang, X., Yin, W., Yu, T., Xue, C., & Wang, A. (2023). Multimodal Machine Learning Guides Low Carbon Aeration Strategies in Urban Wastewater Treatment. *Engineering*. https://doi.org/10.1016/j.eng.2023.11.020

[28] Abudu, H., Wesseh, P. K., & Lin, B. (2024). Journal of Management Science and Engineering Climate bonds toward achieving net zero emissions and carbon neutrality : Evidence from machine learning technique. *Journal of Management Science and Engineering*, *9*(1), 1–15. https://doi.org/10.1016/j.jmse.2023.10.001

[29] Ferreira, E., Macedo, E., Fernandes, P., & Coelho, M. C. (2023). A combined framework of Biplots and Machine Learning for real-world driving volatility and emissions data interpretation. *Sustainable Cities and Society*, *99*(April), 104945. https://doi.org/10.1016/j.scs.2023.104945

[30] Hussin, F., Aqilah, S., Rahim, N., Syahirah, N., Hatta, M., Kheireddine, M., & Ali, S. (2023). Review article A systematic review of machine learning approaches in carbon capture applications. *Journal of CO2 Utilization*, *71*(5), 102474. https://doi.org/10.1016/j.jcou.2023.102474