INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 10 ISSUE: 04 | APRIL - 2026 SJIF RATING: 8.659 ISSN: 2582-3930

IMPACT OF ML IN CARBON FOOTPRINT CALCULATION

P.V Kishore [1], K.Lakshmi Dheeraja[2], A.Dhanusree[3], V.Mohan Sri Ram[4]

[1,2,3]Department of Electronics and Communication Engineering/KL University/India

Abstract

In today's world, carbon footprints play a significant role in environmental discussions. The term "carbon footprint" refers to the total amount of carbon dioxide emissions produced by industries, individuals, and various sectors. Reducing carbon emissions contributes to a cleaner and healthier environment. Numerous studies have explored different methods and techniques for calculating these emissions. This project focuses on calculating carbon footprints using data science and Python, a versatile programming language. The front-end is designed using HTML, while machine learning techniques are employed for the analysis. The code runs upon receiving input and provides comprehensive calculations of historical emissions and their contributions to atmospheric carbon levels.

Keywords: carbon footprint, HTML, Python..

I. INTRODUCTION

1.1 Machine learning :

The power of machine learning (ML), a subfield of artificial intelligence, is to create systems that can identify patterns in data and make predictions or judgments without the need for human interaction. It seeks to improve production efficiency, dependability, and quality. Machine learning is proven to be a crucial tool in areas including healthcare, banking, transportation, and telecommunications as data becomes more widely available.

With applications in robotics, gaming, and self-driving cars, reinforcement learning teaches systems through trial and error by rewarding or punishing models based on their behavior. Neural networks, random forests, support vector machines, decision trees, and linear regression are all combined in different ways. Natural language processing and speech recognition are two areas where deep learning, a more sophisticated subset of machine learning that makes use of multi-layer neural networks, shines.

Automation, improved decision-making, and the development of more intelligent systems are all results of machine learning's ongoing evolution. Machine learning will be essential to industry optimization, user experience personalization, and solving challenging real-world problems as technology develops.

1.2 Linear Regression :

One of the most basic machine learning methods is linear regression, which models the connection between input variables (features) and a continuous output variable. For prediction tasks, it is straightforward but effective because it assumes a linear relationship between them. The linear regression general equation is

(y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_nx_n + \epsilon)------(1)

where (y) is the dependent variable, (x_i) are the independent variables, and (\beta_i) are the weights or coefficients

and the error term is represented by (\epsilon).

The algorithm's objective is to reduce the discrepancy between expected and actual values; Ordinary Least Squares (OLS) is frequently used to accomplish this. Simple linear regression, which uses a single independent variable which uses a single independent variable, and multiple linear regression ,which uses several independent variables are the two types are linear regression.

The algorithm's objective is to reduce the discrepancy between expected and actual values; Ordinary Least Squares (OLS) is frequently used to accomplish this. Simple linear regression, which uses a single independent variable, and multiple linear regression, which uses several independent variables, are the two types of linear regression.

Predictions may become less accurate and reliable when these presumptions are broken. Despite its simplicity, linear regression has a wide range of uses, including forecasting stock prices in finance, predicting student performance in education, estimating recovery durations in healthcare, and projecting sales and demand in business. Nevertheless, it has drawbacks, including dependence on rigid assumptions, susceptibility to outliers, and inappropriateness for non-linear interactions. All things considered, linear regression is still a very comprehensible, effective, and popular approach for continuous prediction problems, particularly when the connection between variables is actually linear.

1.3 HTML :

Front-end HTML development is primarily responsible for creating the interactive and visible portions of a website. HTML, or HyperText Markup Language, is used to organize text, images, links, tables, forms, and multimedia on web pages. Any website you see online is built on HTML, which is often combined with Javascript and CSS.

The fact that HTML is platform-independent—that is, compatible with all browsers and devices—is one of its advantages. Advanced features and as well as semantic tags and were added to modern HTML versions, particularly HTML5. These semantic elements improve readability for both developers and search engines, enhancing accessibility and SEO performance.

Front-end HTML development is closely linked to JavaScript and CSS (Cascading Style Sheets). While HTML provides structure, CSS adds design elements like colors, fonts, layouts, and responsiveness. JavaScript adds interaction to enable features like sliders, form validation, and dynamic content updates. They comprise the core stack for front-end development. HTML is easy to learn and appropriate for novices. It's a great location for students and aspiring web developers to start because it doesn't require programming logic. HTML continues to play a significant role in the development of websites, along with frameworks and technologies like React, Angular, and Bootstrap that still rely on HTML syntax.

2 LITERATURE SURVEY :

Xu et al. (2024) study how to use machine learning models like Random Forest, XGBoost, and Neural Networks to guess how much carbon homes will release. The study employs household-level data and examines spatial variables such as building size, density, and structure. The results show that XGBoost gives the most accurate predictions, which shows how well ensemble learning methods work. The study also finds that the way space is designed has a big effect on carbon emissions and suggests ways to lower them. Other related studies confirm that machine learning models surpass conventional statistical methods by identifying intricate, non-linear relationships. Most previous research has concentrated on urban locales, whereas Xu et al. highlight emissions from rural residences.

Jiang et al. (2022) examine the carbon footprint of household activities through a time-use methodology, offering greater detail than conventional expenditure-based approaches. The study looks at about 85 daily activities and how much energy and carbon emissions are used for each one. The research groups activities like cooking, cleaning, bathing, getting around, and having fun, and then looks at how much each one adds to total emissions. The results show that transportation and energy-intensive activities at home are the biggest contributors to household carbon footprints. It also shows that carbon emissions vary between weekdays and weekends, with higher emissions observed during weekends due to increased leisure and travel activities.

3 METHODOLOGY:

```
from flask import Flask, request, render_template
import joblib
import pandas as pd
app = Flask(__name__)
model = joblib.load("carbon_footprint_model.pkl")
@app.route("/", methods=["GET", "POST"])
def index():
    result = None
    if request.method == "POST":
        data = {
            "Transport": request.form["Transport"],
            "Diet": request.form["Diet"],
```

```
            "Vehicle Type": request.form["Vehicle Type"],
            "Monthly Grocery Bill": int(request.form["Monthly Grocery Bill"]),
            "Vehicle Monthly Distance Km": int(request.form["Vehicle Monthly Distance Km"])
        }
        df = pd.DataFrame([data])
        prediction = model.predict(df)[0]
        result = round(prediction, 2)
return render_template("index.html", prediction=result)if __name__ == "__main__":
    app.run(debug=True)
```

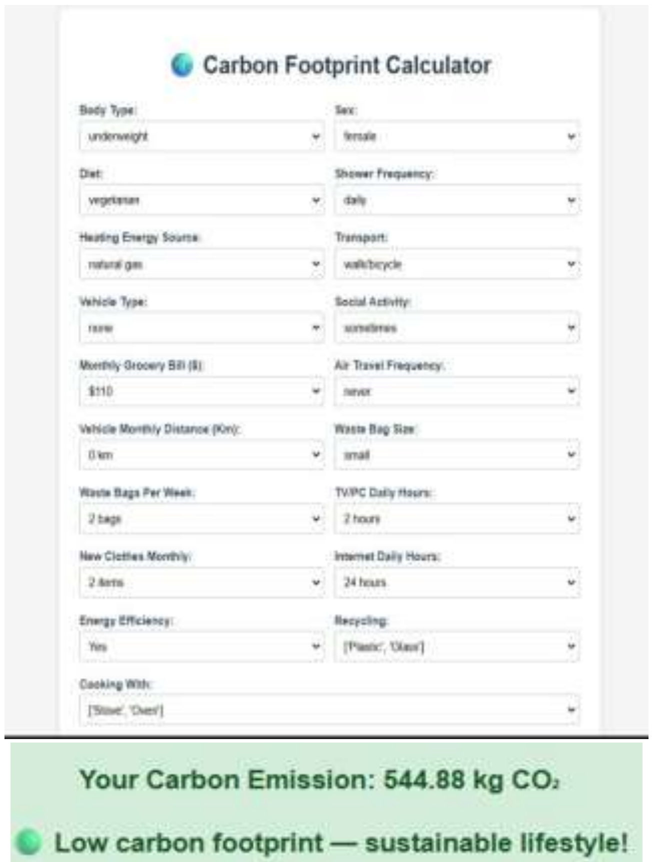

Fig 3.1 Requirements to calculate the CFP

4 RESULTS AND DISCUSSIONS :

Body Type	Sex	Diet	How Often Showe	Heating Energy Source		Vehicle Type	Social Activity	Monthly Grocery Bill	Frequency of	Vehicle Monthly	Waste Bag Size	Waste Bag Weekly Count	How Long TV PC Daily Hour
overweight	female	pescatarian	daily	coal	public		often	230	frequently	210	large	4	7
obese	female	vegetarian	less frequently	natural gas	walk/bicycle		often	114	rarely	9	extra large	3	9
overweight	male	omnivore	more frequently	wood	private	petrol	never	138	never	2472	small	1	14
overweight	male	omnivore	twice a day	wood	walk/bicycle		sometimes	157	rarely	74	medium	3	20
obese	female	vegetarian	daily	coal	private	diesel	often	266	very frequent	8457	large	1	3
overweight	male	vegetarian	less frequently	wood	public		sometimes	144	frequently	658	large	1	22
underweight	female	vegan	less frequently	wood	private	hybrid	never	56	rarely	5363	medium	4	9
underweight	female	vegan	more frequently	coal	walk/bicycle		sometimes	59	very frequent	54	extra large	3	5
overweight	male	omnivore	daily	wood	public		never	200	frequently	1376	medium	3	3
underweight	female	pescatarian	daily	wood	public		often	135	rarely	440	extra large	1	8
normal	female	vegetarian	more frequently	wood	public		never	146	never	1561	extra large	4	12
obese	male	vegetarian	more frequently	coal	walk/bicycle		never	111	very frequent	69	medium	5	9
underweight	female	omnivore	twice a day	coal	walk/bicycle		often	114	rarely	92	large	3	18
underweight	female	vegan	less frequently	electricity	private	lpg	sometimes	111	rarely	2893	large	6	13
obese	male	pescatarian	less frequently	natural gas	public		often	123	rarely	1989	small	6	13
overweight	female	vegetarian	less frequently	electricity	public		never	225	very frequent	692	small	6	9
normal	male	pescatarian	more frequently	electricity	walk/bicycle		often	219	frequently	7	extra large	4	23
overweight	female	pescatarian	daily	wood	public		often	104	rarely	948	large	6	1
underweight	male	vegan	more frequently	electricity	private	petrol	often	126	very frequent	7622	medium	2	6
normal	female	omnivore	more frequently	wood	walk/bicycle		often	288	never	51	small	4	15
normal	male	vegan	twice a day	electricity	private	electric	often	282	rarely	2237	large	6	0
obese	female	pescatarian	less frequently	wood	public		never	69	rarely	1804	large	1	6
overweight	male	omnivore	twice a day	wood	walk/bicycle		sometimes	110	never	85	small	3	14

Table 4.1.1 Output information based on CFP Process

How Many New Clothes Monthly	How Long Internet Daily Hour	Energy efficiency	Recycling	Cooking_With	CarbonEmission
26	1	No	['Metal']	['Stove', 'Oven']	2238
38	5	No	['Metal']	['Stove', 'Microwave']	1892
47	6	Sometimes	['Metal']	['Oven', 'Microwave']	2595
5	7	Sometimes	['Paper', 'Plastic', 'Glass', 'Metal']	['Microwave', 'Grill', 'Airfryer']	1074
5	6	Yes	['Paper']	['Oven']	4743
18	9	Sometimes	['Paper', 'Glass', 'Metal']	['Stove', 'Oven', 'Microwave']	1647
11	19	Sometimes	[]	['Grill', 'Airfryer']	1832
39	15	No	['Paper', 'Plastic', 'Glass']	['Stove', 'Microwave']	2322
31	15	Yes	['Glass']	['Microwave', 'Grill', 'Airfryer']	2494
23	18	Sometimes	['Glass']	['Microwave', 'Grill', 'Airfryer']	1178
27	21	No	['Paper', 'Plastic']	['Stove', 'Microwave']	1427
4	4	Sometimes	[]	['Stove', 'Oven', 'Microwave']	3226
27	4	Yes	['Plastic']	['Stove']	1593
16	10	Sometimes	['Plastic', 'Glass', 'Metal']	['Stove', 'Oven', 'Microwave', 'Grill', 'Airfryer']	1732
23	8	No	['Paper', 'Plastic', 'Metal']	['Stove', 'Oven']	1743
24	15	No	['Paper', 'Plastic', 'Glass', 'Metal']	['Stove', 'Oven']	2101
42	14	Sometimes	[]	['Oven', 'Microwave', 'Grill', 'Airfryer']	2609
6	22	Yes	['Paper']	['Stove', 'Grill', 'Airfryer']	1565
37	9	Sometimes	[]	['Stove']	5272
22	6	No	['Paper', 'Glass', 'Metal']	['Stove', 'Oven']	1220
8	5	No	['Plastic', 'Glass', 'Metal']	['Oven', 'Grill', 'Airfryer']	1300
3	7	No	['Metal']	['Stove', 'Oven', 'Microwave']	1024

Table 4.1.2 Output information based on CFP Process

The above table consists of CFP information of individual urban homes .It consists of Bodytype,Sex,diet,heating energy, source, vehicle type, social activity, monthly grocery bill, wasteage bag weekly count, recycling, cooking_with, how many new clothes monthly,how long internet daily hour,energy efficiency, carbonemission and column consists of its properties.

5. CONCLUSION:

Carbon footprint calculation and analysis are essential for climate action planning. By measuring emissions and identifying reduction opportunities, individuals and organizations can make informed decisions that contribute to a sustainable and environmentally responsible future. Carbon footprint analysis involves identifying high-emission sources, tracking monthly or annual emission patterns, comparing baseline and reduced emissions, and evaluating operational sustainability and efficiency. Lifecycle assessments (LCA), emission reports, and dashboards are examples of data visualization technologies that help organizations better understand their impact.

6.References :

[1] C. Sun, Y. Zhang, W. Ma, R. Wu, and S. Wang, "The impacts of urban form on carbon emissions: A comprehensive review," *Land*, vol. 11, no. 9, p. 1430, 2022.

[2] Z. Zhao and A. Ramaswami, "Community-wide greenhouse gas emissions inventory and consumption-based footprint accounting: A case study of Xiamen City, China," *Environmental Research Letters*, vol. 10, no. 5, p. 054001, 2015.

[3] S. Ebner, N. Charron, and J. Thé, "A city-wide greenhouse gas emissions inventory for Montreal: Insights for urban carbon mitigation," *Environmental Systems Research*, vol. 13, no. 1, p. 341, 2024.

[4] C. Zhang and Y. Lin, "Urbanization and carbon emissions: A panel data analysis (1961–2011) across 141 countries," *Energy Policy*, vol. 100, pp. 453–468, 2017.

[5] K. S. Sridhar, "Urbanization and carbon emissions in India and China," *Environment and Urbanization Asia*, vol. 9, no. 2, pp. 178–194, 2018.

[6] Wiedenhofer, D., Guan, D., Liu, Z., Meng, J., Zhang, N., & Wei, Y. M. (2017). The effect of urbanization on China's carbon footprint: A multiregional input–output analysis. Ecological Economics, 142, 1–13.

[7] D. Kennedy, C. Steinberger, B. Gasson, Y. Hansen, and R. Hillman, "Greenhouse gas emissions from global cities," *Environmental Science & Technology*, vol. 43, no. 19, pp. 7297–7302, 2009.

[8] H. Seto, B. Güneralp, and L. Hutyra, "Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools," *Proceedings of the National Academy of Sciences*, vol. 109, no. 40, pp. 16083–16088, 2012.

[9] P. Fragkias, K. C. Seto, E. L. Satterthwaite, and S. Harlan, "Urbanization and global environmental change," *Annual Review of Environment and Resources*, vol. 38, pp. 45–69, 2013.

[10] Y. Ding, K.-J. Cao, Z.-Z. Guo, J.-L. Dong, S.-X. Zhou, and Z.-P. Lu, "Urban carbon emissions: Evolution, analysis, and application based on 53-year data," *Frontiers in Public Health*, vol. 13, p. 1713278, 2025.