10.48047/jocaaa.2024.33.05.81

A Hybrid Machine Learning Approach to Dynamic Carbon Footprint Modeling and Predictive Analytics

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Abstract

As climate change accelerates, accurate carbon footprint management is vital for achieving global sustainability goals. Traditionally, carbon accounting has relied on static, standardized emission factors and manual data compilation methods established in the late 1990s. While foundational, these approaches often yield generalized estimates that fail to account for localized variations, real-time operational shifts, or complex data integration. Consequently, organizations and policymakers face significant challenges in tracking progress and executing precise reduction strategies. To overcome these limitations, this project develops an integrated framework for dynamic carbon footprint analysis and modeling. By leveraging advanced data analytics, Internet of Things (IoT) sensors, and machine learning, the proposed system transitions carbon accounting from static estimations to real-time, actionable insights. This framework automates data integration from diverse sources, significantly reducing manual reporting errors and increasing assessment precision. Ultimately, this research provides a responsive, scalable approach to managing greenhouse gas emissions, enhancing the efficacy of corporate and civic carbon reduction strategies, and supporting broader environmental sustainability initiatives.

Keywords: Carbon Footprint Modeling, Sustainable Environment, Machine Learning, Real-Time Emission Tracking, Predictive Analytics

1. Introduction

The concept of the carbon footprint has undergone a major paradigm shift since its emergence in the late 1990s. Early methodologies relied on broad, macro-level estimates and static emission factors. For instance, initial baseline calculations estimated the carbon footprint of an average passenger vehicle at approximately 0.25 kg CO_2 per mile based on generalized fuel consumption data. While these early frameworks established a foundational awareness of environmental impacts, they lacked the granularity required for targeted interventions. By the early 2000s, the introduction of detailed emission inventories and sector-specific data drastically improved accounting precision. A key milestone occurred with the publication of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, which provided a comprehensive, tier-based methodology for classifying emission sources and incorporating refined activity data. In recent years, the paradigm has shifted toward real-time, dynamic environmental analytics. The convergence of Big Data, IoT infrastructure, and advanced analytical modeling enables modern systems to track emissions with unprecedented specificity. Contemporary platforms can monitor individual manufacturing lines or specific product lifecycles in near real-time. Recent literature indicates that incorporating machine learning models not only minimizes forecasting errors but also allows organizations to proactively adapt their sustainability strategies. Despite these technological leaps, significant challenges persist regarding the seamless integration of disparate data streams and the accurate calibration of models to reflect regional grid variances.

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1.1 Motivation

The motivation for optimizing carbon footprint analysis is rooted in the urgent global mandate to mitigate climate change. Traditional accounting frameworks fall short of providing the localized, time-sensitive data required for high-stakes decision-making. Static emission factors fail to capture rapid shifts in regional energy mixes, supply chain disruptions, or technological upgrades, often resulting in skewed environmental assessments. As regulatory pressures intensify and corporate social responsibility (CSR) compliance becomes mandatory, organizations require precise tools rather than approximations. By integrating machine learning and dynamic analytical modeling, this research aims to bridge the gap between compliance-driven reporting and real-time operational optimization, fostering more agile carbon management.

1.2 Problem Statement

Traditional, manual approaches to carbon footprint analysis are constrained by systematic inefficiencies. The primary limitation is an over-reliance on standardized emission factors and static databases, which overlook localized geographical or operational anomalies. Furthermore, manual data collection is inherently labour-intensive, slow, and highly susceptible to human error, rendering the resulting metrics outdated by the time they are published. Traditional databases cannot dynamically adjust to abrupt operational changes or integrate heterogeneous data streams seamlessly. Without automation and predictive modeling, stakeholders lack the responsive infrastructure necessary to evaluate climate policy efficacy or track progress toward net-zero targets reliably.

2. Literature Review

The development of accurate frameworks for evaluating and mitigating greenhouse gas (GHG) emissions requires a multi-scale understanding of global policy targets, macro-level sectoral trends, and emerging technological interventions. This section synthesizes existing literature across global environmental baselines, macro-transportation trends, and advanced technological strategies designed to decouple economic growth from carbon intensity.

2.1 Global Emission Baselines and Climate Mitigation Frameworks

Macro-level environmental tracking provides the boundary conditions necessary for localized carbon footprint modeling. Reports from foundational international bodies establish the urgency and baseline metrics for tracking greenhouse gases. The International Energy Agency (IEA) [1] provided a comprehensive assessment of global CO2 emission trends for 2022, detailing the distribution of emissions across industrial and energy sectors. This report underscored the critical reality that despite expanding global decarbonization rhetoric, emissions continue to rise, highlighting an acute need for more stringent climate policies and responsive data infrastructures.

Complementing these tracking mechanisms, the Intergovernmental Panel on Climate Change (IPCC) [2] presented its definitive "Climate Change 2022: Mitigation of Climate Change" report. The IPCC outlined actionable, cross-sectoral pathways required to stabilize global temperatures, emphasizing that the efficacy of any mitigation strategy rests heavily on an organization’s or nation's ability to precisely measure, audit, and adapt to emission fluctuations. Furthermore, the World Resources Institute (WRI) [4], in its "State of Climate Action 2022" publication, evaluated the alignment of current global climate initiatives against the long-term goals of the Paris Agreement. The WRI findings explicitly pinpointed massive implementation gaps, concluding that a lack of granular, real-time tracking data frequently handicaps policymakers from evaluating the compliance and success of localized climate action plans.

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2.2 Transportation Sector Emission Dynamics

Because transportation represents one of the largest and fastest-growing sources of global greenhouse gas emissions, its modeling demands specialized attention. The International Transport Forum (ITF) [3], through the "ITF Transport Outlook 2023," provided comprehensive future projections regarding global travel demands and associated carbon outputs. The outlook established that standard, static modeling approaches fail to capture the behavioral variations and multimodal shifts inherent in modern logistics.

To understand the systemic shocks that affect these macro-models, Jefferson [13] conducted an analysis of the structural challenges that the COVID-19 pandemic imposed on global oil supply, demand, and pricing structures. Jefferson's work demonstrated how rapidly global energy dynamics can pivot, rendering static, manual emissions databases obsolete and underscoring the necessity of automated, real-time analytic frameworks that adjust dynamically to macroeconomic anomalies.

2.3 Road Decarbonization and Electrification Roadmaps

Transitioning road transit from internal combustion engines to alternative powertrains represents a primary lever for carbon reduction, though its execution introduces complex variables to standard emissions inventories. Kok et al. [5] examined the tactical acceleration of zero-emission vehicle (ZEV) adoption specifically within commercial fleets. Their findings indicated that while fleet electrification offers a high-impact pathway to road transport decarbonization, the actual net savings are highly variable and contingent on localized routing and charging behaviors.

Expanding on this spatial variability, Vega-Perkins et al. [6] mapped the multi-faceted impacts of electric vehicles (EVs) on regional GHG emissions, consumer fuel costs, and energy justice across the United States. Their research proved that the environmental benefits of EVs are not uniform; rather, they depend heavily on the carbon intensity of the local electrical grid. This variability necessitates the integration of dynamic grid emission factors into any modern carbon footprint model.

To map the long-term trajectory of these shifts, the International Energy Agency (IEA) [14] released the "Global EV Outlook 2020," tracking global market penetration, infrastructure deficits, and recommendations for scaling EV ecosystems. These metrics are further augmented by consumer-centric market intelligence platforms, such as Wards Intelligence [12] and the "McKinsey Electric Vehicle Index" presented by Gersdorf et al. [19], which quantify how economic disruptions and regional consumer behavior dictate the actual rate of vehicle adoption and, consequently, the real-time deflection of emissions curves.

2.4 Alternative Fuel Paradigms and Infrastructure Constraints

While electrification dominates passenger transport discourse, heavier logistical sectors require alternative fuel infrastructures that present unique modeling challenges. The scalability of the hydrogen sector, for example, demands meticulous strategic oversight. McDowall [7] developed advanced technology roadmaps to manage transitions into the hydrogen energy sector, detailing how structured frameworks can guide the deployment of production and distribution logistics. Similarly, Amer and Daim [8] applied technology roadmaps to broader renewable energy sectors, illustrating how strategic planning helps overcome the localized deployment bottlenecks that frequently skew static carbon accounting models.

On a broader industrial scale, Zhang et al. [9] evaluated technology roadmaps for carbon capture, utilization, and storage (CCUS) frameworks within China, highlighting the massive capital and technical infrastructure required to successfully integrate carbon-negative technologies into existing grids. This macro-technological perspective is supported by the IEA's "Energy Technology

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Perspectives 2020" [10], which explored the broad innovations required to drive cross-sectoral energy transitions.

On the infrastructure side, alternative liquid fuels offer an immediate, drop-in mechanism for reducing carbon footprints, though their supply chains are complex to audit. Knecht [17] analyzed the highly successful Brazilian retail ethanol infrastructure, offering it as a scalable blueprint for the United States while noting the deep dependencies on regional agricultural and logistical networks. To evaluate the systemic validity of these fuels, Hasan et al. [18] conducted extensive bibliometric research mapping the global sustainable biofuel economy. Their study revealed a sharp research trend focused on capturing the full lifecycle impacts of biofuels, pointing out that manual accounting systems frequently omit upstream supply chain emissions, thereby distorting the perceived sustainability of the fuel.

2.5 Industrial, Maritime, Aviation, and Rail Decarbonization

Comprehensive environmental modeling must also capture non-road and heavy transport modalities, which exhibit distinct operational profiles:

- **Non-Road Mobile Machinery:** Notter et al. [11] addressed a critical gap in traditional emissions accounting by compiling a specialized emissions inventory for non-road mobile machinery across the construction and agricultural sectors. Their research underscored that non-road machinery contributes a disproportionate volume of localized particulate and greenhouse gas emissions, yet it remains largely obscured in generalized national databases.
- **Aviation:** In the aviation sector, alternative fuels represent the primary viable path to near-term decarbonization. The "Sustainable Aviation Fuels Fact Sheet" [22] outlined the baseline environmental advantages and scalability constraints of non-petroleum jet fuels. Doliente et al. [23] expanded on this by executing a comprehensive supply-chain component analysis for bio-aviation fuel production, illustrating that a fuel's true carbon mitigation potential is strictly bound to its upstream processing and refining efficiencies.
- **Maritime Transport:** For international shipping, the International Maritime Organization (IMO) [24] established stringent action plans and regulatory strategies to systematically curb greenhouse gas emissions across global maritime corridors, pushing the industry toward automated tracking of vessel fuel efficiency.
- **Rail Infrastructure:** Finally, within the rail sector, Zenith et al. [25] performed a techno-economic analysis comparing freight railway electrification via traditional overhead lines against emerging hydrogen fuel cells and heavy-duty battery packs. Utilizing case studies from Norway and the United States, their work demonstrated that the optimal, lowest-carbon rail solution is entirely dependent on track topology, traffic density, and regional energy availability.

Summary of Findings

As established across the literature, from macro-level climate directives [2] down to machinery-specific inventories [11], current carbon accounting remains fragmented. Traditional frameworks rely on static, historical datasets that completely miss real-time regional grid variations [6], supply chain disruptions [13], or localized operational parameters [5]. This clear gap in the literature highlights the immediate necessity for the integrated, machine learning-driven, and dynamic carbon footprint modeling framework proposed in this study.

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3. Proposed System

The proposed architecture establishes an automated, end-to-end machine learning pipeline designed to ingest raw environmental and operational data, execute robust preprocessing, and employ predictive algorithms to model carbon emissions. The system balances predictive precision with dynamic scalability by implementing parallel training and validation pathways.

The comprehensive methodology is systematically structured into five core procedural phases, as mapped in the sequence below.

1. Data Acquisition and Exploratory Analysis: Ingestion of heterogeneous emission records, structural validation, and initial statistical profiling.

2. Advanced Data Preprocessing: Handling missing values, categorical encoding, class rebalancing via resampling, and feature-target isolation.

3. Model Training and Optimization: Parallel training of baseline Linear Regression and optimized XGBoost Regressor models with persistent serialization.

4. Out-of-Sample Evaluation: Ingestion of completely unseen validation streams (test.csv) to test model generalization under live deployment conditions.

5. Performance Metrics Assessment: Statistical quantification of error distributions using MAE, MSE, RMSE, and R2 scores to isolate the optimal predictive architecture.

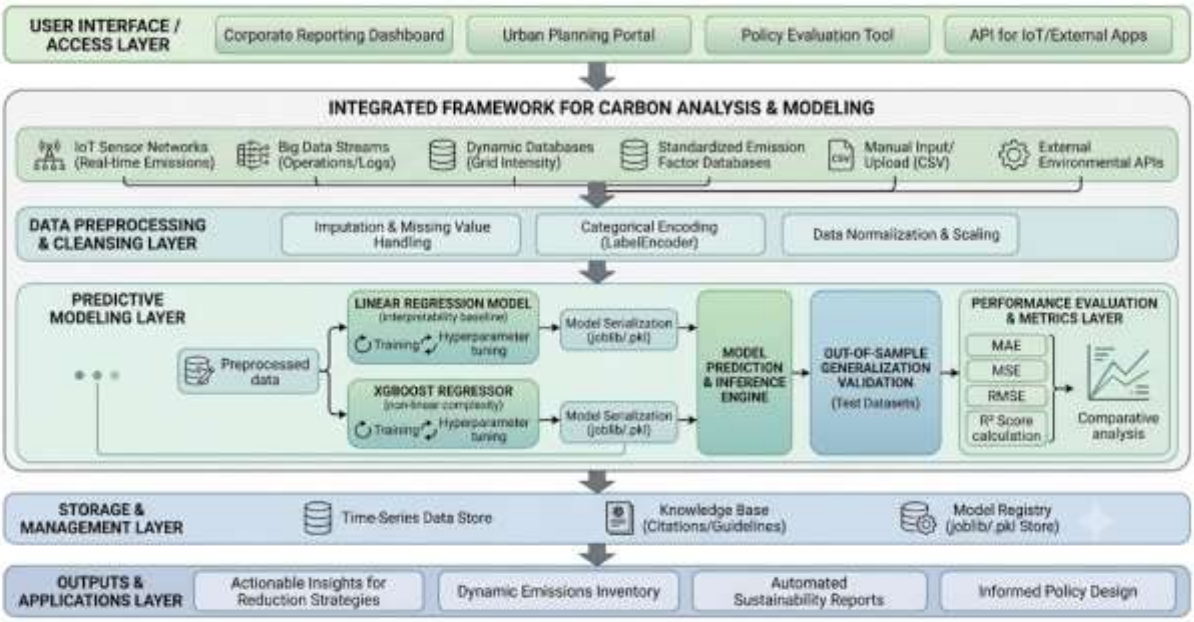

Fig. 1: Proposed system architecture of dynamic carbon footprint modelling framework.

3.1 Data Acquisition and Exploratory Profiling

The computational pipeline initializes with the programmatic ingestion of the primary environmental dataset, Carbon Emission.csv, utilizing high-performance data manipulation libraries including Pandas and NumPy. Upon ingestion, structural integrity verification is executed by evaluating the data types, verifying non-null matrix dimensions, and checking for duplicate tuples. Descriptive statistical profiling is conducted across all continuous and discrete features to map variance, skewness, and kurtosis. Finally, the target feature vector representing total carbon emissions is extracted, and its underlying probability density function (PDF) is visualized to detect anomalies and identify potential long-tailed distributions.

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4. Results and Discussion

Figure 2 displays a sample of the raw carbon emission dataset. It includes columns such as Body Type, Sex, Diet, How Often Shower, Heating Energy Source, Transport, Vehicle Type, Social Activity, Monthly Grocery Bill, Frequency of Traveling by Air, Vehicle Monthly Distance Km, Waste Bag Size, Waste Bag Weekly Count, How Long TV PC Daily Hour, How Many New Clothes Monthly, How Long Internet Daily Hour, Energy Efficiency, Recycling, Cooking With, and CarbonEmission. This sample provides an initial view of the data structure and content, highlighting key features and target variables.

Body Type	Sex	Diet	How Often Shower	Heating Energy Source	Transport	Vehicle Type	Social Activity	Monthly Grocery Bill	Frequency of Traveling by Air	Vehicle Monthly Distance Km	Waste Bag Size	Waste Bag Weekly Count	How Long TV PC Daily Hour	How Many New Clothes Monthly	How Long Internet Daily Hour	Energy efficiency	Recycling	Cooking_With	CarbonEmission
overweight	female	pescatarian	daily	coal	public	NaN	often	230	frequently	210	large	4	7	26	1	No	['Metal']	['Stove', 'Oven']	2238
obese	female	vegetarian	less frequently	natural gas	walk/bicycle	NaN	often	114	rarely	9	extra large	3	9	38	5	No	['Metal']	['Stove', 'Microwave']	1892
overweight	male	omnivore	more frequently	wood	private	petrol	never	138	never	2472	small	1	14	47	6	Sometimes	['Metal']	['Oven', 'Microwave']	2595
overweight	male	omnivore	twice a day	wood	walk/bicycle	NaN	sometimes	157	rarely	74	medium	3	20	5	7	Sometimes	['Paper', 'Plastic', 'Glass', 'Metal']	['Microwave', 'Grill', 'Airfryer']	1074
obese	female	vegetarian	daily	coal	private	diesel	often	266	very frequently	8457	large	1	3	5	6	Yes	['Paper']	['Oven']	4743

Figure 2: Sample uploaded dataset.

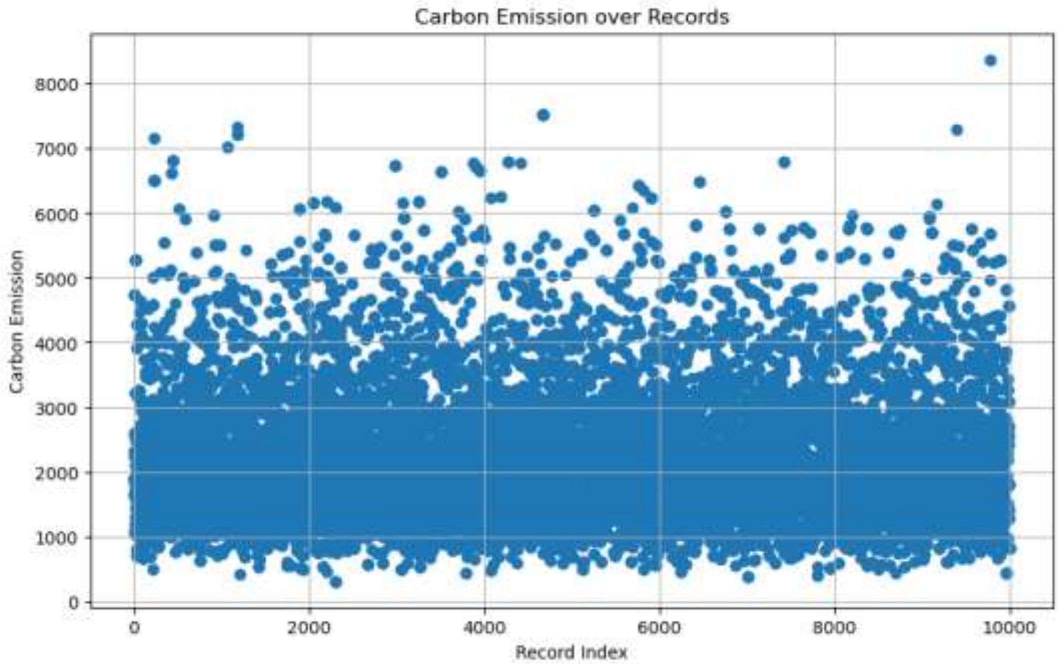

Figure 3: Distribution of Carbon Emission

Figure 3 presents a scatter plot of carbon emissions over the dataset records. This visualization helps in understanding the distribution and range of carbon emission values, providing insights into the variability and trends in carbon emissions across different records.

Body Type	Sex	Diet	How Often Shower	Heating Energy Source	Transport	Vehicle Type	Social Activity	Monthly Grocery Bill	Frequency of Traveling by Air	Vehicle Monthly Distance Km	Waste Bag Size	Waste Bag Weekly Count	How Long TV PC Daily Hour	How Many New Clothes Monthly	How Long Internet Daily Hour	Energy efficiency	Recycling	Cooking_With	CarbonEmission
2	0	1	0	0	1	0	1	230	0	210	1	4	7	26	1	0	2	13	2238
1	0	3	1	2	2	0	1	114	2	9	0	3	9	38	5	0	2	9	1892
2	1	0	2	3	5	3	0	138	1	2472	3	1	14	47	6	1	2	5	2595
2	1	0	3	3	2	0	2	157	2	74	2	3	20	5	7	1	8	1	1074
1	0	3	0	0	0	1	1	266	3	8457	1	1	3	5	6	2	10	6	4743

Figure 4: Data Preprocessing by Label Encoding

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Figure 4 shows the effect of Label Encoding applied to categorical variables. It demonstrates how categorical features such as Vehicle Type and Diet are converted into numerical values to prepare the data for machine learning algorithms. This transformation is crucial for enabling the use of these features in predictive modeling.

	Body Type	Sex	Diet	How Often Shower	Heating Energy Source	Transport	Vehicle Type	Social Activity	Monthly Grocery Bill	Frequency of Traveling by Air	Vehicle Monthly Distance Km	Waste Bag Size	Waste Bag Weekly Count	How Long TV PC Daily Hour	How Many New Clothes Monthly	How Long Internet Daily Hour	Energy efficiency	Recycling	Cooking_With	CarbonEmission
7270	2	0	3	3	2	0	1	3	91	2	1898	0	5	17	22	1	0	5	3	2356
840	1	0	1	2	3	2	0	3	226	0	31	0	4	5	25	23	0	14	7	2547
5200	2	0	3	0	2	0	1	3	38	0	1216	2	3	10	15	17	2	6	2	1568
5191	2	0	0	2	0	1	0	3	151	2	1861	3	2	7	1	23	1	9	5	1308
5134	2	1	1	1	0	0	2	1	114	2	3711	2	5	8	19	16	0	11	14	1761
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
6034	1	1	1	3	3	1	0	1	208	1	1573	0	4	1	33	11	0	6	9	2073
9876	3	3	2	3	0	2	0	3	264	1	87	0	3	18	42	3	0	11	12	1274
5230	1	0	2	2	1	1	0	2	64	3	664	3	2	12	6	16	2	13	15	1965
9936	2	0	0	3	3	2	0	2	68	3	36	1	5	15	4	18	2	7	2	2228
4834	1	0	0	0	2	1	0	1	55	1	1220	1	1	3	22	13	2	7	2	1064

22000 rows × 20 columns

Figure 5: Resampling to Balance the Dataset

Figure 5 depicts the balanced dataset after resampling. It shows the increased sample size and balanced class distribution, addressing potential issues of class imbalance. This visualization is important for ensuring that the model training process is not biased towards any particular class.

```
pretrained model is loaded
Linear Regressor model Mean Absolute Error : 531.1282065204309
Linear Regressor model Mean Squared Error  : 435289.4512872438
Linear Regressor model Root Mean Squared Error : 659.7646938774792
Linear Regressor model R² Score : 0.5881438514336562
```

Figure 6: Model Performance Metrics - Linear Regression

Figure 6 presents the performance metrics for the Linear Regression model. This includes Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 Score. The metrics are visualized to evaluate how well the Linear Regression model predicts carbon emissions compared to the actual values.

```
Model loaded successfully.
XGBoostRegressor Mean Absolute Error : 62.01163366144354
XGBoostRegressor Mean Squared Error  : 8715.025813536004
XGBoostRegressor Root Mean Squared Error : 93.35430259787711
XGBoostRegressor R² Score : 0.9917541374926391
```

Figure 7: Model Performance Metrics - XGBoost Regressor

Figure 7 displays the performance metrics for the XGBoost Regressor model. Similar to Figure 6, it includes MAE, MSE, RMSE, and R^2 Score. This figure highlights the superior performance of XGBoost in predicting carbon emissions, showing its effectiveness compared to the Linear Regression model.

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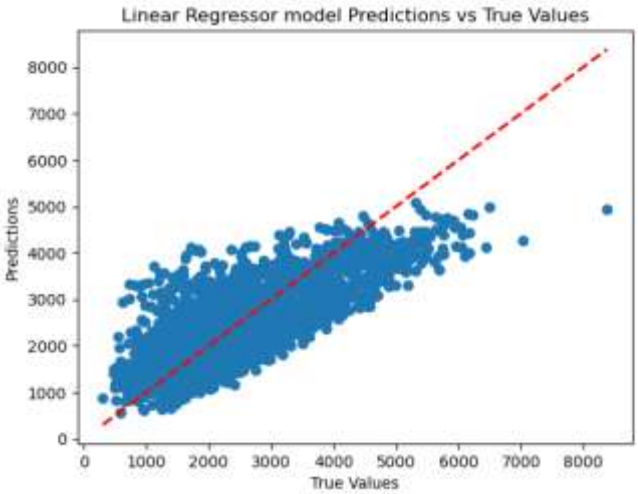

Figure 8: Predictions vs True Values - Linear Regression

Figure 8 provides a scatter plot comparing the predicted carbon emissions versus the true values for the Linear Regression model. The best-fit line is included to visualize the model's accuracy and alignment with actual values. This figure helps in assessing how well the Linear Regression model performs in predicting carbon emissions.

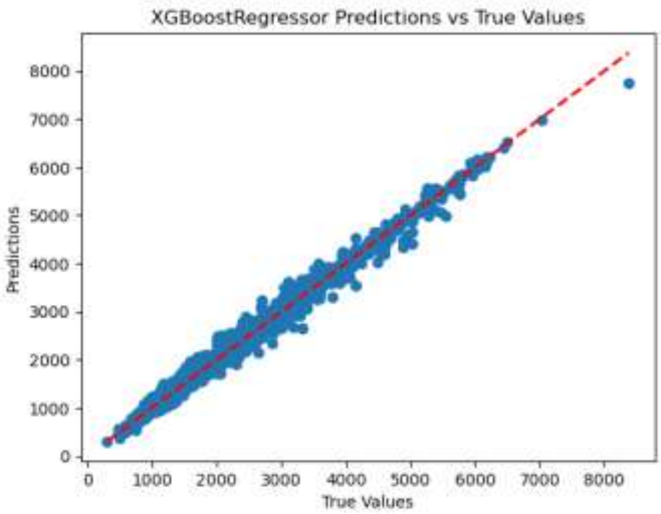

Figure 9: Predictions vs True Values - XGBoost Regressor

Figure 9 presents a scatter plot for the XGBoost Regressor model, comparing the predicted carbon emissions with the true values. The inclusion of the best-fit line demonstrates the accuracy and effectiveness of XGBoost in making predictions. This visualization is used to compare the prediction performance of XGBoost with Linear Regression.

Body Type	Sex	Diet	How Often Shower	Heating Energy Source	Transport	Vehicle Type	Social Activity	Monthly Grocery Bill	Frequency of Traveling by Air	Vehicle Monthly Distance Km	Waste Bag Size	Waste Bag Weekly Count	How Long TV PC Daily Hour	How Many New Clothes Monthly	How Long Internet Daily Hour	Energy efficiency	Recycling	Cooking_With	Predicted
1	0	1	0	0	1	2	1	230	0	210	1	4	7	28	1	0	1	6	2602.123047
0	0	3	1	1	3	2	1	114	2	9	0	3	9	38	5	0	1	4	1406.720703
1	1	0	2	2	0	1	0	138	1	3472	3	1	14	47	6	1	1	2	2156.523682
1	1	0	3	2	3	2	2	157	2	74	2	3	20	5	7	1	3	1	1376.676025
0	0	3	0	0	0	0	1	266	3	8457	1	1	3	5	6	2	3	3	4302.523438
1	1	3	1	2	1	2	2	144	0	658	1	1	22	16	9	1	2	5	1961.295509
2	0	2	1	2	0	1	0	56	2	3263	2	4	8	11	19	1	8	0	2440.528809
2	0	2	2	0	3	2	2	59	3	54	0	3	1	38	15	0	4	4	2808.859375
1	1	0	0	2	1	2	0	200	0	1376	2	3	3	31	15	2	0	1	2263.600098

Figure 10: Test Data Predictions.

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Figure 10 shows the test dataset with predictions appended. It includes the actual data alongside the predicted carbon emissions from the XGBoost model. This figure illustrates how the model's predictions are integrated into the test data, providing a comprehensive view of the model's performance on new data.

5. Conclusion

The research successfully demonstrates the application of machine learning models, specifically Linear Regression and XGBoost Regressor, for predicting carbon emissions based on various lifestyle and behavioral features. Through a comprehensive data preprocessing phase that included handling missing values, encoding categorical variables, and resampling, the dataset was prepared for effective model training. The evaluation of both models revealed that XGBoost Regressor outperforms Linear Regression, with superior performance metrics such as lower Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), and a higher R^2 Score. This indicates that XGBoost is more adept at capturing complex patterns and interactions in the data, providing more accurate predictions of carbon emissions. The findings highlight the importance of using advanced machine learning techniques for environmental impact assessments. The integration of dynamic data sources and sophisticated analytical methods has proven to be crucial for achieving accurate and actionable insights. The project demonstrates the effectiveness of leveraging modern algorithms to improve the precision of carbon footprint assessments, which is essential for developing effective carbon reduction strategies and advancing environmental sustainability efforts.

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