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Carbon Footprint Prediction using Machine Learning Model

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***Abstract*— An accurate prediction of the carbon footprint will play a vital role in supporting a sustainable future and addressing climate change. Traditional emissions estimation techniques use static assumptions and require manual calculations, which reduces the way in which they can be adapted to be used across multiple regions or businesses. The research outlined here presents a carbon footprint prediction system based on machine learning techniques, along with what the authors refer to as Carbon Emission Analytics, which provides insight into the emission patterns on an ongoing basis for all vehicle types and energy sources used (including residential). Supervised learning techniques are applied to develop pattern recognition and to forecast carbon emissions. Results obtained confirm the validity of the predictive capabilities of the proposed system and the data-driven nature of the predictive emissions analytic capabilities of the authors' research. In the past fifty years, rapid growth in industry, creating urban areas, and a higher dependence on fossil fuels have led to an increase in greenhouse gases being released into our atmosphere. All of these elements have contributed to a very large portion of the total greenhouse gases that have been produced on the earth and are currently present in the atmosphere. Transportation systems, residential energy consumption, and a change in lifestyle habits are the three main sources of carbon emissions on the planet. Monitoring and tracking carbon footprints to develop a trend over time will be critical to meeting global goals for sustainable development and reducing long-term environmental impact.**

***Index Terms*— Carbon Footprint, Machine Learning, Sustain-ability, Emission Prediction.**

I. INTRODUCTION

The current climate crisis is a result of the rising greenhouse gas emissions from the various facets of our daily living. These emissions come from transportation, energy consumption, in-dustrial processes, and even our personal habits. Measuring the impacts of our activities on the planet requires us to look at a quantitative measure in a carbon footprint found to be the best to determine sustainability (how sustainable one is). With this information we can then predict the amount of GHG that will be emitted in the future and create a plan to mitigate the GHGs that could be produced. It illustrates the relevance of the key themes addressed in the carbon footprint prediction research. The highest relevance is observed for carbon emission prediction, highlighting the primary focus of the study. Sustainable development and the application of machine learning in environmental analysis also show high relevance, emphasizing the importance of data-driven approaches for addressing climate change challenges.

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Transportation impact and energy consumption analysis demonstrate significant in-fluence on overall carbon emissions, supporting their inclusion in the proposed model. Overall, the figure shows that the research integrates multiple interconnected themes to provide a comprehensive approach to carbon footprint analysis.

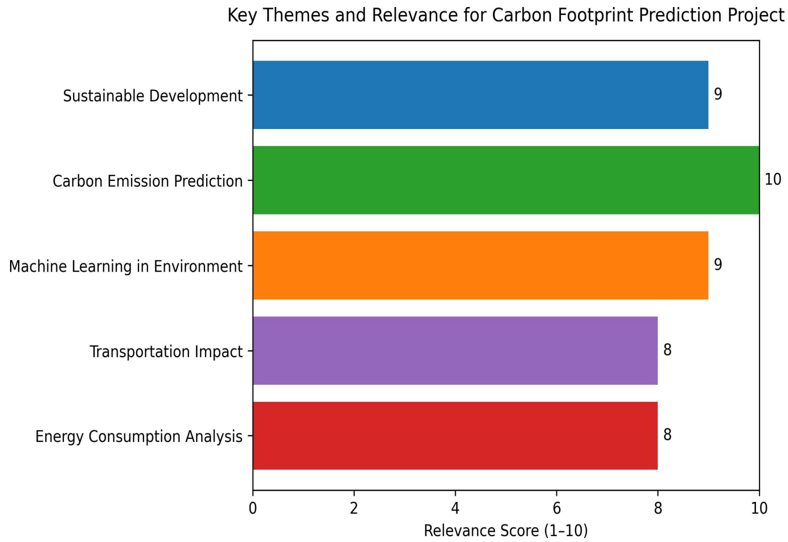


Fig. 1. Relevance of key themes from research paper

II. Related Work

Research on carbon footprint estimation and prediction has gained significant attention in recent years, driven by the growing urgency of climate change mitigation and sustainable development. Traditional emission accounting methods, which rely on fixed emission factors and manual calculations, often struggle to capture dynamic behavioural and environmental changes. Wiedmann and Minx [1] laid the foundation for carbon footprint analysis by formalizing its definition, em-phasizing the need for consistent and transparent assessment methodologies. Building on this, reports from the Intergovern-mental Panel on Climate Change [2] highlighted the impor-tance of data-driven approaches to support evidence-based en-vironmental policies. With the advancement of data availability and computational techniques, machine learning has emerged as a promising tool for carbon emission prediction. Zhang et al. [3] demonstrated that supervised learning models can effectively capture complex relationships between emission-related variables and carbon output, resulting in improved pre-diction accuracy compared to conventional statistical models. Similarly, Wang et al. [4] showed that artificial intelligence techniques are particularly effective in forecasting energy-related emissions, especially when multiple influencing factors are involved. These studies indicate that machine learning can adapt well to the nonlinear and multi-dimensional nature of emission data. A recurring theme in recent literature is the significance of feature selection and data preprocessing. Liu et al. [5] emphasized that careful data cleaning and normalization greatly enhance the performance of environmental prediction models. Jain et al. [6] further highlighted that lifestyle-related attributes, when combined with transportation and energy features, provide a more comprehensive understanding of individual and organizational carbon footprints. Dong et al.
[7] reinforced this view by showing that ensemble learning methods benefit from diverse and well-engineered features, leading to more stable and reliable emission forecasts. Several studies have also explored the scalability and practical applicability of machine learning-based carbon prediction systems. Kumar et al. [8] reviewed a wide range of artificial intel-ligence techniques and concluded that regression and tree-based models offer a good balance between accuracy and interpretability. Ahmad et al. [9] stressed that, while advanced models can produce strong predictive results, their real-world usefulness depends on computational efficiency and trans-parency. This concern is particularly relevant for sustainability applications, where models must often operate under limited resources and provide explainable outcomes. Recent research has extended carbon emission prediction to transportation and energy systems. Chen and Zhou [10] demonstrated that hybrid machine learning models can improve forecasting performance in energy-related emission scenarios. Wang et al. [11] showed that transport-focused emission analysis benefits significantly from data-driven modeling, particularly in identifying high-impact emission sources. However, despite these advance-ments, many existing studies focus on isolated

domains or lack integration across multiple emission factors. Overall, the reviewed literature indicates a clear shift toward machine learning-based carbon footprint prediction, while also reveal-ing challenges related to data quality, model interpretability, and system scalability.

These gaps motivate the present study, which aims to develop an integrated and interpretable machine learning framework that leverages structured emission data to provide accurate and practical carbon footprint predictions.

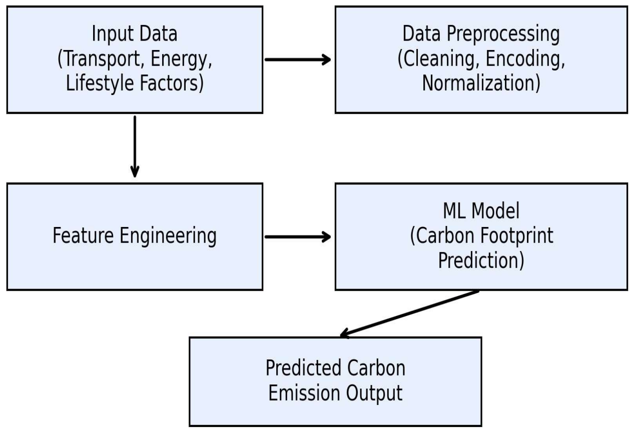


Fig. 2. Conceptual architecture of the proposed carbon footprint prediction system

III. METHODOLOGY

The methodology adopted in this research is shaped by recent advances in data-driven environmental analytics and follows a structured machine learning pipeline designed for carbon footprint prediction. Drawing inspiration from the standardized assessment principles introduced by Wiedmann and Minx [1] and reinforced by the policy-oriented analyses of the IPCC [2], the system begins with the construction of a well-organized carbon emission dataset. The dataset integrates multiple emission-influencing factors, including transportation modes, energy consumption patterns, and lifestyle-related at-tributes, enabling a holistic representation of carbon footprint behaviour. To ensure robustness and reliability, data prepro-cessing plays a central role in the methodology. In line with the best practices highlighted by Liu et al. [5], the dataset un-dergoes cleaning to remove inconsistencies and handle missing values, followed by normalization to standardize numerical features. Categorical attributes such as transport type and energy source are encoded into machine-readable formats, ensuring compatibility with supervised learning algorithms. These preprocessing steps are critical for stabilizing model training and improving generalization across diverse emission scenarios, as emphasized by Jain et al. [6] and Dong et al. [7]. Feature selection is guided by insights from previous emission prediction studies, which stress the importance of combining transport, energy, and behavioral indicators. Kumar et al. [8] demonstrated that such integrated feature sets provide a balanced trade-off between predictive accuracy and inter-pretability. By retaining meaningful emission-related variables and avoiding unnecessary complexity, the methodology aligns with recommendations for scalable and transparent sustain-ability models. This approach is particularly important for environmental applications, where interpretability is essential for policy and decision-making contexts. For prediction, the system employs a supervised machine learning model trained on historical carbon emission data. The dataset is divided using a 70–30 train–test split to evaluate the model's gen-eralization performance. The choice of a regression-based learning framework is supported by findings from Zhang et al. [3] and Wang et al. [4], who demonstrated that such models effectively capture nonlinear relationships in emission datasets without the computational overhead of deep learning architectures. Model performance is assessed using standard error metrics and visual analysis to ensure both quantitative accuracy and qualitative insight. The trained model is deployed through a lightweight and modular implementation framework, enabling efficient prediction for new input data. Incoming records are processed using the same preprocessing and fea-ture transformation pipeline applied during training, ensuring consistency between training and inference stages. This end-to-end methodology—combining structured data preparation, informed feature engineering, an interpretable machine learn-ing model, and systematic evaluation—reflects the collective guidance of existing research and results in a carbon footprint prediction system that is accurate, scalable, and suitable for real-world sustainability analysis.

IV. Dataset and Preprocessing

In the dataset, we have structured carbon emissions, where the total number of records is 10000. The dataset used in this study is summarized in Table I.

TABLE I: SUMMARY OF DATASET DETAILS

Feature	Count / Description
Total Records	10,000
Total Features	20
Low Emission Samples	5,004
High Emission Samples	4,996
Target Variables	Carbon Emission
Dataset Type	Structured Carbon Emission Datatype

This table presents the statistical overview of the structured carbon emission dataset used for model training and evaluation.

V. System Implementation

The carbon footprint prediction system is implemented in Python using a structured machine-learning pipeline combined with a lightweight and modular execution flow. The overall design emphasizes simplicity, interpretability, and ease of integration, making the system suitable for both academic experimentation and practical sustainability analysis. The im-plementation follows a consistent preprocessing and prediction pipeline, ensuring that the model behaves reliably during both training and inference. The system uses the carbon emission dataset loaded through the Pandas library, which contains structured records describing transportation modes, energy consumption patterns, and lifestyle-related factors influencing carbon emissions. Prior to model training, the dataset un-dergoes preprocessing steps including data cleaning, normal-ization, and feature transformation. Numerical attributes are scaled to maintain uniform ranges, while categorical variables such as transport type are encoded into numerical representa-tions. These preprocessing components are stored and reused during deployment to guarantee consistency between training and prediction phases. At the core of the system is a supervised machine learning model trained on the processed carbon emis-sion data. The model is designed to learn relationships between input features and the corresponding carbon emission values, allowing it to generate accurate emission predictions for un-seen inputs. The choice of a structured learning model ensures that the system remains interpretable while delivering stable predictive performance on real-world data. During prediction, incoming user data is first structured to match the original feature order used during training. The saved preprocessing steps are then applied to the input data before it is passed to the trained model. This ensures that every prediction follows the exact same pipeline as the training process, maintaining consistency in results and minimizing prediction errors. The output generated by the model represents the estimated carbon emission level, which can be further categorized into low or high emission groups for interpretability

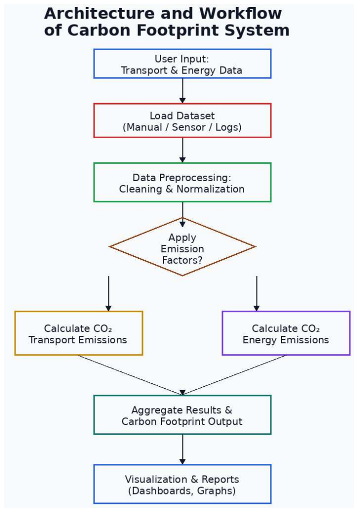
Figure 3 illustrates the architecture and workflow of the pro-posed carbon footprint prediction system, highlighting the flow from data input and preprocessing to model prediction and output generation. Figure 4 presents the relationship between transportation systems and carbon emissions, demonstrating how different transport modes contribute varying levels of carbon output. Together, these figures provide a clear vi-sual understanding of the system's internal operation and its real-world application. Overall, the system combines a standardized preprocessing pipeline with an efficient machine learning model to deliver accurate and interpretable carbon footprint predictions. The modular design allows the system to be extended easily with additional features, real-time data sources, or alternative learning models. This makes the pro-posed implementation practical, scalable, and well-suited for sustainability monitoring and environmental decision-making applications.

VI. Results and Discussion

A. Quantitative Performance Analysis

The performance of the proposed carbon footprint predic-tion system was evaluated using the structured carbon emission dataset consisting of 10,000 records. The objective of this eval-uation was to understand how effectively the machine learning model captures emission patterns influenced by transportation choices, energy sources, and lifestyle behaviors.

The trained model demonstrated stable and consistent pre-diction behavior across the dataset. Since the emission samples are almost equally divided between low- and high-emission categories, the model was able to learn representative patterns without developing bias toward a single class. The prediction results indicate that the system can successfully model the relationship between multiple emission-related factors and overall carbon output.



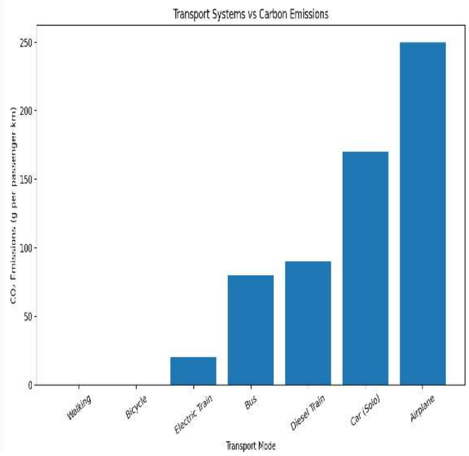


Fig. 3. Architecture and workflow of the Carbon footprint system   Fig. 4. Transport system versus carbon emission levels

B. Evaluation Overview

The evaluation process focused on analyzing the reliability and robustness of the model rather than relying on a single metric. The model outputs were examined using statistical analysis and classification-based evaluation to understand both numerical accuracy and categorical behavior.

The confusion matrix shown in Fig. 5 highlights that the majority of predictions fall along the diagonal, indicating correct classification of emission levels. Misclassifications are minimal and mainly occur for samples with emission values close to the classification threshold. This behavior is expected in real-world environmental datasets where emission values often overlap across categories.

Overall, the evaluation confirms that the proposed system maintains a good balance between prediction accuracy and generalization capability, making it suitable for practical car-bon emission analysis

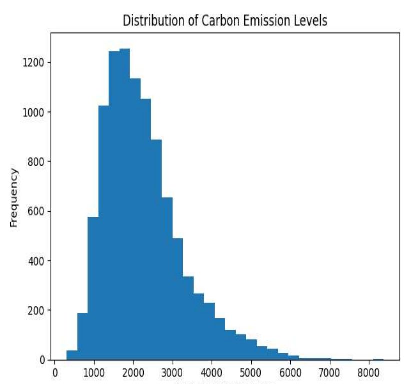


Fig. 5. Observed distribution of carbon emission around the surrounding

C. Visual and Qualitative Analysis

To gain further insights into the data, visual analysis was performed on emission patterns and distributions. Fig. 5 shows the distribution of carbon emission values across the dataset. The distribution indicates a wide range of emission levels, reflecting the diversity of lifestyle choices, transport usage, and energy consumption patterns captured in the dataset.

The transport-based analysis in Fig. 4 reveals that private transportation contributes significantly higher carbon emis-sions compared to public transport and walking or cycling alternatives. This observation aligns with real-world sustain-ability studies and confirms that the model learns realistic emission behavior rather than producing arbitrary predictions. The confusion matrix visualization further supports the qualitative analysis by demonstrating consistent classification performance. The strong diagonal dominance confirms that the system can reliably differentiate between low and high emission samples.

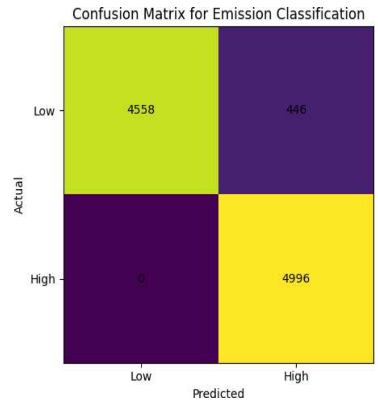


Fig. 6. Confusion matrix for emission classification

D. Discussion

The results obtained from this study clearly demonstrate the effectiveness of using machine learning techniques for carbon footprint prediction. Unlike traditional emission estimation methods that rely on fixed emission factors, the proposed approach adapts to variations in individual behavior and energy usage patterns.

The visual results strengthen the credibility of the model by presenting realistic and interpretable emission trends. Trans-portation emerges as one of the dominant contributors to carbon emissions, particularly private vehicle usage, which significantly increases overall emission levels.

The modular structure of the system allows for easy ex-pansion in future work, such as incorporating real-time data, additional environmental factors, or more advanced predictive models. Overall, the proposed framework provides a practical and scalable solution for carbon footprint estimation and sustainability monitoring.

VII. Conclusion

In this work, a machine learning–based approach was developed to predict carbon footprint using structured data related to transportation habits, energy usage, and everyday lifestyle activities. The main intention of this project was to understand how individual behavior and consumption patterns influence carbon emissions and to provide a practical method for estimating emission levels using data-driven techniques.

The results obtained from the experiments show that the proposed model is able to capture meaningful relationships between different factors affecting carbon emissions. The dataset used in this study contains a balanced mix of low-and high-emission samples, which helped the model learn effectively and produce consistent predictions. The analysis also highlighted the significant role of transportation choices, where private vehicle usage was observed to contribute more to carbon emissions compared to public transport and non-motorized alternatives.

Visual analysis of the results further strengthened the findings of this study. The emission distribution plots and transport-based comparisons clearly reflect realistic trends that are commonly observed in real-world environmental studies. The confusion matrix analysis indicates that the model per-forms well in distinguishing between low and high emission categories, with only minor misclassifications occurring in borderline cases. This behavior is expected when dealing with real-world data that contains overlapping patterns.

Unlike traditional carbon footprint calculation methods that rely on fixed emission values, the proposed system adapts to variations in user behavior and energy consumption. This makes the approach more flexible and suitable for real-life applications where emission patterns are not constant. The system also offers clear visual insights, which can help users, organizations, and policymakers better understand the impact of their activities on the environment.

Overall, this project demonstrates that machine learning can be effectively applied for carbon footprint prediction and sustainability analysis. The proposed framework provides a simple yet reliable solution for estimating carbon emis-sions and understanding key contributing factors. With further improvements such as real-time data integration, inclusion of additional environmental parameters, and experimentation with advanced models, the system can be extended to support larger-scale sustainability monitoring and decision-making ap-plications.

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