International Journal of Advance Research in Science and Engineering
Volume. No. 15, Issue No. 05, May, 2026
ISSN: 2319-8354

# AN EXPLAINABLE-AI BASED ANALYSIS OF VEHICLE CHARACTERSTICS FOR CO2-EMISSION ESTIMATION

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***Abstract*— Carbon dioxide($CO_2$) emissions from vehicles are a major contributor to climate change, making it important to understand which vehicle features most affect emissions. While machine learning models can predict emissions with high accuracy, they often act as "black boxes," limiting their usefulness for decision-making.This project combines regression models (Random Forest, Gradient Boosting, and SVR) with Explainable AI techniques (SHAP, LIME, and ALIBI) to build an interpretable $CO_2$ prediction system. Using a 29-year dataset (1995–2023) with around 27,000 records, the system analyzes features such as engine size, fuel type, transmission, and fuel consumption.The models achieve high accuracy ($R^2 \approx 0.999$ for Random Forest and Gradient Boosting), while XAI reveals that combined fuel consumption is the most influential factor, followed by fuel type, engine size, and model year. The results highlight trends such as lower emissions in newer vehicles and higher emissions in premium brands, providing actionable insights for reducing automotive carbon footprints.**

***Keywords*— Explainable AI, XAI, SHAP, LIME, ALIBI, CO2 Emissions, Vehicle Characteristics, Random Forest, Gradient Boosting, Support Vector Regression, Feature Importance, Transfer Learning,**

## I. INTRODUCTION

Climate change driven by greenhouse gas emissions is a major global challenge, with the transportation sector contributing about 24% of $CO_2$ emissions from fuel combustion. Road vehicles are the largest contributors, making it essential to understand how vehicle characteristics affect emissions. This knowledge supports better decision-making for policymakers, manufacturers, and consumers to reduce environmental impact.

Machine learning models such as Random Forest, Gradient Boosting, and SVR can predict $CO_2$ emissions with very high accuracy ($R^2 > 0.99$). However, these models often act as "black boxes," providing predictions without explaining the factors behind them. This lack of transparency limits their practical use in policy and design decisions where understanding feature impact is crucial.

Explainable Artificial Intelligence (XAI) addresses this issue by providing both global and local explanations of model behavior. Techniques like SHAP, LIME, and ALIBI help identify key factors influencing emissions and explain individual predictions. By combining ML with XAI, the system offers both high accuracy and interpretability, enabling more informed and trustworthy decisions.

This project uses a 29-year dataset (1995–2023) of vehicle fuel consumption from Natural Resources Canada, containing around 27,000 records. It develops an interpretable $CO_2$ prediction system that achieves high accuracy, identifies important features such as fuel type and engine size, and provides actionable insights for reducing emissions.

## II. LITERATURE SURVEY

Carbon dioxide is the primary anthropogenic greenhouse gas, accounting for approximately 76% of total greenhouse gas emissions. The transportation sector is the third-largest emitting sector globally,and road transport (passenger vehicles and freight) dominates transport emissions. Vehicle CO2 emissions are directly proportional to fuel consumption: burning one litre of gasoline produces approximately 2.3 kg of CO2, while one litre of diesel produces approximately 2.7 kg of CO2. The relationship between fuel consumption and CO2 emissions is governed by the carbon content of the fuel and the combustion stoichiometry.

CO2 (g/km) = Fuel Consumption (L/100km) × Emission Factor (g/L) / 100

Machine Learning for Emission Prediction

Random Forest Regression

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the average prediction across all trees. Each tree is built on a bootstrap sample of the training data (bagging), and at each split, a random subset of features is considered. This double randomness reduces overfitting and variance while maintaining low bias.

$$\{y\} = (1/B) \sum_{\{b=1\}}^{\{B\}} T\_b(x)$$

where B is the number of trees and T_b is the prediction of the b-th tree. Feature importance is computed as the total decrease in impurity (Gini or variance) attributed to each feature across all trees.

**a. Gradient Boosting Regression**

Gradient Boosting builds an ensemble of weak learners (typically shallow decision trees) sequentially, with each new tree correcting the residual errors of the previous ensemble. The model is trained by gradient descent in function space, minimizing a differentiable loss function:

$$F\_m(x) = F\_\{m-1\}(x) + \eta \cdot h\_m(x)$$

where F_m is the ensemble at iteration m, η is the learning rate (0.1 in this project), and h_m is the new weak learner fitted to the negative gradient (pseudo-residuals).

**b. Support Vector Regression (SVR)**

SVR finds a function that deviates from the actual values by at most ε (epsilon), using the RBF(Radial Basis Function) kernel to map inputs to a higher-dimensional feature space where linear regression can be performed:

$$K(x\_i, x\_j) = exp(-\gamma \, ||x\_i - x\_j||^2)5$$

The RBF kernel enables SVR to model non-linear relationships between vehicle features and CO2 emissions.

**c. Explainable AI (XAI) Frameworks**

SHAP (SHapley Additive exPlanations)

SHAP unifies several XAI approaches under a single theoretical framework based on Shapley values from cooperative game theory. The Shapley value for feature j is the average marginal contribution of feature j across all possible feature coalitions:

$$\Phi\_j = \sum\_\{S \subseteq N \backslash \{j\}\} |S|!(|N|-|S|-1)!/|N|! \times [f(S \cup \{j\}) - f(S)]$$

LIME (Local Interpretable Model-agnostic Explanations)

LIME generates local explanations by fitting an interpretable surrogate model (typically linear regression) in the neighborhood of the prediction being explained. It perturbs the input, obtains model predictions for the perturbed samples, and fits a weighted linear model:

$$\xi(x) = argmin\_\{g \in G\} L(f, g, \pi\_x) + \Omega(g)$$

ALIBI(Tree)

ALIBI is a comprehensive XAI library that provides multiple explanation methods. In this project, ALIBI's TreeShap implementation is used for tree-based models (Random Forest, Gradient Boosting), providing exact SHAP value computation using the tree structure. ALIBI's implementation is fitted on a background dataset and provides both global and local explanations.

The key properties of Shapley values that make them ideal for ML explanation are: Efficiency (all feature contributions sum to the total prediction minus the baseline), Symmetry (features that contribute equally receive equal attribution), Dummy (features that contribute nothing receive zero attribution), and Linearity (Shapley values of combined models equal the combination of individual Shapley values). These axiomatic properties guarantee that SHAP explanations are unique and fair.

## III. EXISTING SYSTEM

The existing $CO_2$ emission prediction system uses traditional methods such as Linear Regression and Decision Trees to estimate emissions based on vehicle parameters like engine size, fuel consumption, and cylinders. However, these models cannot effectively handle complex and nonlinear relationships in real-world data, resulting in lower prediction accuracy. The system also lacks advanced preprocessing, feature engineering, and scalability, making it less efficient for large datasets and real-time applications. In addition, it does not provide interpretability, so users cannot understand how different features influence the prediction, reducing transparency and trust.

**Disadvantages of Existing System**

- Low prediction accuracy for complex and nonlinear data.
- Lack of interpretability and transparency in predictions.
- Absence of advanced models and Explainable AI techniques.
- Poor preprocessing and limited scalability for large datasets.

## IV. PROPOSED WORK

The proposed $CO_2$ emission prediction system uses advanced ensemble machine learning models such as Random Forest and Gradient Boosting to improve prediction accuracy and handle complex nonlinear data. The system includes preprocessing techniques like data cleaning, normalization, and feature engineering to enhance data quality and model performance. It also integrates Explainable AI methods such as SHAP, LIME, and ALIBI to explain how each feature affects the prediction. In addition, the system provides visualizations, supports large datasets, and is suitable for real-time applications.

**Advantages of Proposed System**

- High prediction accuracy using advanced models such as Random Forest and Gradient Boosting.
- Improved interpretability through Explainable AI techniques like SHAP, LIME, and ALIBI.
- Better data quality and efficiency through preprocessing and feature engineering.
- Scalable and suitable for large datasets, real-time applications, and visualization of results.

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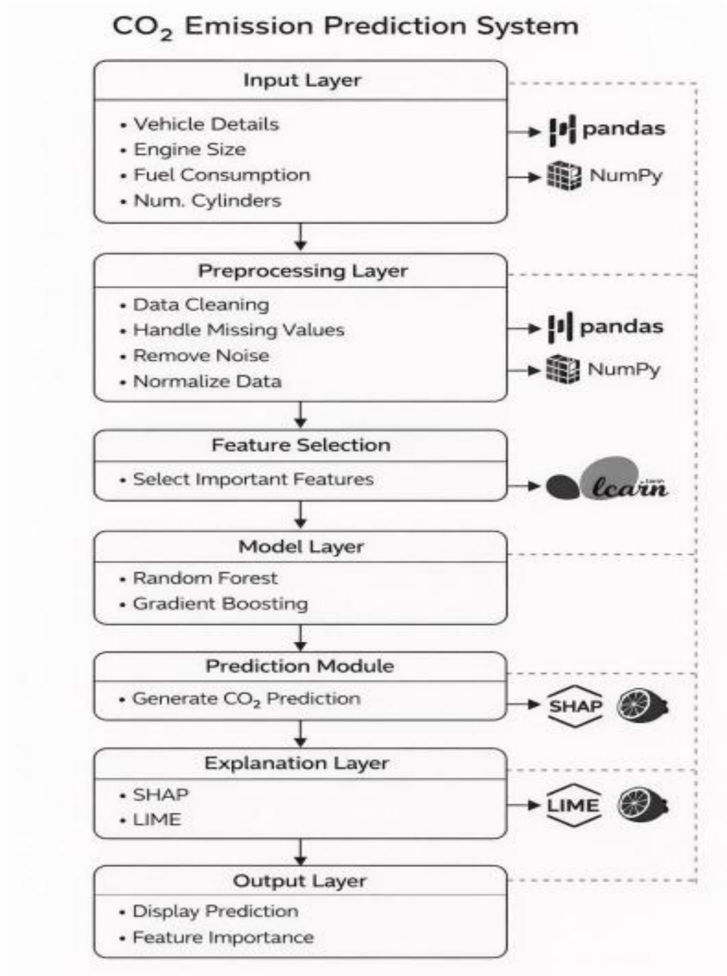


Figure1:System Architecture

## V. LIST OF MODULES

The system is divided into different modules such as input, preprocessing, model, prediction, and explanation. Each module performs a specific function in the $CO_2$ emission prediction process. The preprocessing module handles data cleaning and normalization. The model and prediction modules generate results, while the explanation module provides feature analysis.

- **Data Collection and Dataset Preparation Module:**Vehicle data such as engine size, fuel consumption, and cylinder count is collected from reliable sources and stored in a structured format. The dataset is then cleaned, normalized, and prepared by handling missing values, duplicates, and inconsistencies. Finally, it is split into training and testing sets for accurate model training and evaluation.
- **Data Preprocessing Module:**The preprocessing module improves data quality by handling missing values, removing duplicates, correcting errors, and reducing noise. It also normalizes and transforms the data into a suitable format for machine learning models, ensuring accurate analysis and prediction.
- **Feature Extraction Module:** The feature extraction module identifies important attributes such as engine size, fuel consumption, and number of cylinders that influence $CO_2$ emissions. Irrelevant features are removed to reduce complexity, and the selected features are transformed into a suitable format for machine learning models, improving accuracy and efficiency.
- **Classification Module:**The classification model module builds and trains machine learning models such as Random Forest and Gradient Boosting to predict $CO_2$ emission levels. Using selected features, the models learn patterns from training data and are evaluated on test data to choose the most accurate and reliable model.
- **Result Generation and Storage Module:**The result generation and storage module produces the final $CO_2$ emission prediction using the trained model and displays it in a clear format. It also stores the input data and predicted results in a structured form for future reference and analysis.

## LIMITATIONS

The ML–XAI framework has some limitations. Its accuracy depends on the quality and completeness of input data. Large datasets can make Random Forest models computationally heavy. SHAP and LIME explanations may be complex for non-technical users. Sudden policy changes or external events like natural disasters are hard to capture. Frequent retraining is needed to keep the model updated. Performance may also vary across different regions due to data availability and local emission patterns.

## VI.OUTPUT SCREENS

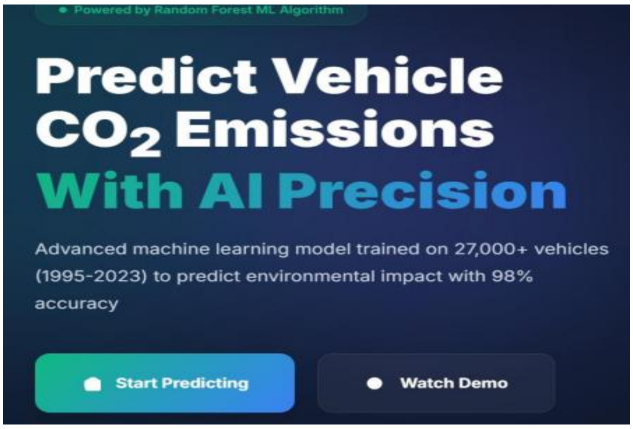


Figure2:Home Screen of the Application

The home screen of the $CO_2$ Emission Prediction web application presents a clean and professional interface that highlights the core functionality of the system. The main heading, "Predict Vehicle $CO_2$ Emissions With AI Precision", immediately informs the user about the purpose of the application. Below the heading, a brief description states: "Advanced machine learning model trained on 27,000+ vehicles (1995–2023) to predict environmental impact with 98% accuracy."

**Predict Vehicle CO2 Emissions**

This interface provides advanced AI-powered predictions for vehicle $CO_2$ emissions. It leverages a Random Forest algorithm trained on over 27,000 vehicles (1995–2023) to estimate emissions accurately. Users can input vehicle specifications such as model year, engine size, number of cylinders, and combined fuel consumption, andcategorize the vehicle type (EcoFriendly, Performance SUV, Hybrid) to generate precise predictions.


Figure3:Predict Vehicle CO2 Emissions


Figure4:Predict Vehicle CO2 Emissions

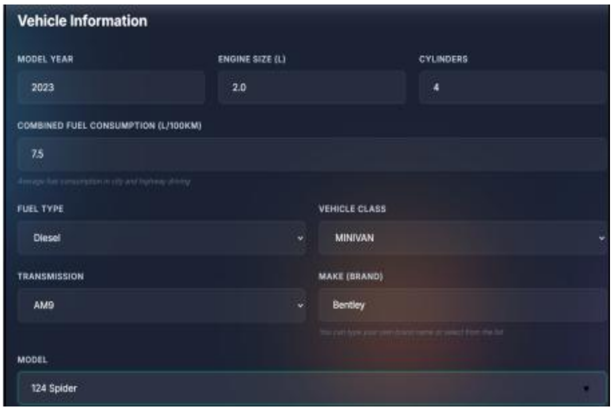


Figure5:Predict Vehicle CO2 Emissions

**Prediction Results – Vehicle $CO_2$ Emissions**

The prediction results provide a clear assessment of a vehicle's $CO_2$ emissions based on the input specifications:

**Predicted Emissions:** 203.3 g/km (classified as **Average**).

**Environmental Impact:** Moderate, with a visible indicator for quick reference.

**Comparison to Average (250 g/km): -18.7% below average**, showing the vehicle performs better than typical emissions.

**Annual $CO_2$ Emissions (assuming 15,000km/year):** 3050 kg (3.05 tonnes).


Figure6:- Prediction Results – Vehicle $CO_2$ Emissions

## VII.CONCLUSION

The project successfully developed an interpretable $CO_2$ emission prediction system using three regression models and three XAI techniques. Random Forest and Gradient Boosting achieved near-perfect accuracy ($R^2 \approx 0.999$), while SHAP, LIME, and ALIBI identified combined fuel consumption as the most important factor affecting $CO_2$ emissions. Overall, the system improves both prediction accuracy and interpretability, supporting sustainable development and environmental protection.

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