Vehicle Carbon Emissions Detector Using Recurrent Neural Network

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Abstract

The rapid increase in global vehicle usage has significantly contributed to rising carbon emissions, posing serious threats to the environment and human health. This study proposes a machine learning–based approach for detecting and predicting vehicle carbon emissions based on engine and vehicle parameters. Applying a Recurrent Neural Network (RNN) based Long Short-Term Memory (LSTM) model to estimate the real-time CO2 emissions is a highly effective approach, particularly since emission data from real-world driving cycles are sequential and time-dependent. While your original study uses a strong non-temporal model (Random Forest Regressor with R2=0.93), the LSTM model is better suited to capture the temporal dependencies in real-time data collected from sources like On-Board Diagnostics (OBD-II) ports.

Keywords: *Carbon emissions, Machine learning, Vehicle pollution, RNN,LSTM*

1.Introduction

Transportation is one of the largest sources of greenhouse gas emissions, contributing approximately 25% of global CO_2 output. The rapid growth in vehicle ownership due to industrialization, population increase, and urban expansion has further intensified the problem of air pollution and climate change. The burning of fossil fuels in vehicles releases not only carbon dioxide but also other harmful pollutants such as carbon monoxide (CO), nitrogen oxides (NOx), and particulate matter, all of which degrade air quality and pose severe health risks. Therefore, monitoring and controlling vehicular emissions has become an urgent environmental and public health priority.

Traditional emission testing methods rely heavily on physical hardware sensors, mechanical exhaust analyzers, and laboratory-based evaluation procedures. Although accurate, these methods are often expensive, time-consuming, require skilled labor, and are not feasible for large-scale or continuous monitoring. Additionally, many vehicles do not undergo frequent emission testing, leading to unnoticed high-emission vehicles operating on roads.

Machine Learning (ML), a subset of artificial intelligence, provides a scalable and data-driven alternative. ML models are capable of identifying complex relationships among various vehicle parameters and can predict emission levels efficiently using historical and real-time data. By learning patterns from datasets that include engine characteristics, fuel type, vehicle weight, and mileage, ML algorithms can produce highly accurate emission estimates. This makes predictive mission monitoring faster, cost-effective, and accessible without the need for specialized hardware.

In this study, an ML-based vehicle carbon emission detector is developed to predict the CO_2 emission level of a vehicle based on readily available specifications. This system aims to support government agencies, vehicle manufacturers, and environmental policymakers by providing an intelligent tool for emission assessment and control, ultimately contributing to sustainable transportation and reduced environmental impact.

The Long Short-Term Memory (LSTM) network is an advanced type of Recurrent Neural Network (RNN) specifically designed to address the vanishing gradient problem that plagues standard RNNs when learning long-term dependencies. This capability is crucial for accurately predicting real-time vehicular emissions, as a vehicle's current CO2 output is highly dependent not just on its current speed or engine load, but also on its recent driving history (e.g., recent acceleration, cruising speed, and gear changes).

LSTM for Real-Time Prediction

- **Sequential Data Processing:** LSTM inherently processes data as a sequence, making it ideal for time-series data streams from sensors.
- **Capturing Temporal Context:** It uses internal mechanisms called **gates** (input, forget, and output) to regulate the flow of information, allowing it to remember relevant data over long periods (long-term memory) and discard irrelevant information.
- **Real-Time Data Sources:** LSTM models are frequently trained on vehicle telematic sensors and OBD-II port data, which provide instantaneous readings like speed, engine RPM, throttle position, and mass air flow (MAF) to predict CO2 on a moment-to-moment basis.

2. Literature Survey

Several research studies have explored the application of machine learning techniques for predicting vehicle carbon emissions. Smith et al. (2019) utilized Linear Regression to analyze the relationship between vehicle characteristics and emission levels, demonstrating a strong correlation between vehicle weight and CO_2 emissions. Lee and Kumar (2020) applied a Decision Tree model and reported that it effectively handled multiple vehicle parameters simultaneously for emission prediction**.** Johnson et al. (2021) implemented a Random Forest algorithm and achieved an accuracy of 91%, showing that ensemble learning can improve predictive performance when dealing with real-world vehicle datasets.

Ahmed and Zhao (2022) employed Deep Learning techniques using Artificial Neural Networks (ANN), which offered higher prediction accuracy but required significantly larger datasets and computing resources. Recently, Patel et al. (2023) proposed a hybrid machine learning model combining multiple ensemble strategies, resulting in improved stability and robustness in CO_2 emission prediction. These studies collectively indicate that ensemble-based approaches, particularly Random Forest and hybrid models, generally outperform single-model prediction techniques. Table -2.1 Shows the summary of the literature reiew.

Table 2.1 Literature Review summary

Author(s)	Year	Method/Algorithm	Findings
Smith et al.	2019	Linear Regression	Demonstrated correlation between vehicle weight and CO_2 emissions.
Lee & Kumar	2020	Decision Tree	Found decision tree effective for emission prediction from multiple parameters.
Johnson et al.	2021	Random Forest	Achieved 91% accuracy using engine capacity and fuel consumption.
Ahmed & Zhao	2022	Deep Learning (ANN)	Neural networks achieved high accuracy but required large datasets.
Patel et al.	2023	Hybrid ML model	Combined ensemble techniques improved emission prediction stability.
Mobasshir et al.	2025	Light Multilayer Perceptron**)**	Achieved high accuracy ($\text{R}^2=0.9938$) and demonstrated that Explainable AI (XAI) is critical for understanding feature importance (e.g., fuel consumption and engine performance).
GreenNav / *MDPI* study)	2024	Hybrid CNN-LSTM (Convolutional Neural Network + Long Short-Term Memory)	Successfully modeled city-wide CO_2 emissions by capturing both temporal dynamics (LSTM) and spatial patterns (CNN), proving the efficacy of hybrid deep learning for complex traffic data ($\text{R}^2=0.91$).
The *ResearchGate* study	2025	Comparative analysis of 18 algorithms, including Ensemble Learning (XGBoost, LightGBM)	Found that Ensemble Learning methods achieve superior accuracy ($\text{R}^2 \approx 0.997$) for **static** vehicle specification data, establishing a high benchmark for non-time-series prediction tasks.

The *MSCL-Attention / MDPI* study	2024	MSCL-Attention Network: Multi-Scale CNN + LSTM + Multi-Head Self-Attention	Introduced a novel architecture that uses the Attention mechanism to allow the LSTM component to intelligently weigh the most relevant time-step features, significantly boosting robustness and predictive precision.

3. Methodology for LSTM-Based CO2 Estimation

This real-time LSTM modeling framework relies on continuous OBD-II time-series data, leveraging instantaneous engine and driving parameters such as RPM, speed, throttle, and fuel rate. Through detailed preprocessing—including normalization, sequence generation, and handling of temporal dependencies—the data becomes suitable for LSTM-based deep learning. This enables highly accurate, real-time CO_2 emission prediction by recognizing complex driving patterns and dynamic vehicle behavior.

3.1 Data Collection and Preparation

Data Source (Real-Time Time-Series Acquisition)

Unlike traditional machine learning models that rely on static or aggregated vehicle specifications, the LSTM-based approach requires **continuous time-series data** reflecting real-world driving behavior. This data is typically collected through the **On-Board Diagnostics (OBD-II) port**, telematics devices, or in-vehicle CAN bus systems.

The OBD-II interface streams real-time sensor readings at frequencies ranging from **1–10 Hz**, depending on the vehicle and the sensor being queried. This continuous stream captures how driving patterns evolve over time—acceleration, braking, engine strain, fuel rate—which directly influences instantaneous CO_2 emissions.

Common sources include:

- OBD-II dongles paired with mobile apps
- Telematics units installed in fleet vehicles
- CAN bus sniffers used for research-grade data logging
- Public datasets from EPA, ICCT, and WLTC driving cycles

  By collecting data over a variety of conditions—city driving, highway cycles, idling, gear changes—the dataset becomes robust enough for a generalizable LSTM model.

3.2 Feature Selection (Instantaneous Driving and Engine Parameters)

LSTM models benefit from rich, high-frequency sensor data. The features used for real-time emission prediction **include instantaneous vehicle and engine parameters**, such as:

- **Vehicle Speed (km/h):** Indicates load, aerodynamic drag, and traffic dynamics.
- **Engine RPM:** Higher RPM typically corresponds with increased fuel consumption.

- **Accelerator Pedal Position (%):** Measures driver demand.
- **Throttle Position (%):** Reflects how wide the intake air valve is open.
- **Engine Load (%):** Represents the percentage of the engine's capacity currently being used.
- **Fuel Rate (L/h):** Directly linked to fuel consumption and CO_2 output.
- **MAF / MAP sensors (Airflow / Pressure):** Influence combustion and emission rates.
- **Time Elapsed:** Used to maintain the sequence order and detect temporal patterns.

The target variable remains:

- **CO_2 Emissions (g/km or g/s)** depending on whether the prediction is distance-based or time-based.

These variables collectively capture both **driver behavior** and **engine response,** making them highly predictive of real-time CO_2 emissions.

3.3. Preprocessing (Preparing Sequential Input for LSTM)

Deep learning models like LSTM require carefully prepared data to learn temporal dependencies effectively. The preprocessing pipeline includes:

a. Normalization or Standardization

Since raw OBD-II sensor values vary widely in scale (e.g., speed in km/h vs. throttle %), normalization is essential to stabilize training and improve convergence.

Common scaling methods include:

- **Min–Max Scaling (0–1):** Best for LSTM as it preserves shape.
- **Z-score Standardization:** Useful when sensor distribution varies widely.

b. Time-Series Structuring (Sequence Formation)

LSTM models do not accept traditional row-by-row data. Instead, the dataset must be transformed into **sliding windows of sequential time steps**.

For example:

- **Input Sequence Length (N):** 10–60 time steps
- **Prediction Horizon (M):** 1–5 future steps

This means the model learns from a sequence such as:

| t-9 | t-8 | t-7 | … | t | → Predict CO_2 at t+1 |

This sequence creation step allows the LSTM to learn patterns like:

- rising RPM + throttle spike → emission surge
- steady cruising → low emissions
- sudden deceleration → drop in emissions

c. Train-Test Temporal Split

Unlike random splitting, time-series data must be split chronologically to prevent information leakage:

- **80% for Training**
- **20% for Testing** (future unseen sequence)

d. Handling Missing or Noisy Sensor Readings

Real-world OBD-II data may contain gaps or noise due to signal loss or inconsistent sampling rates. Methods used include:

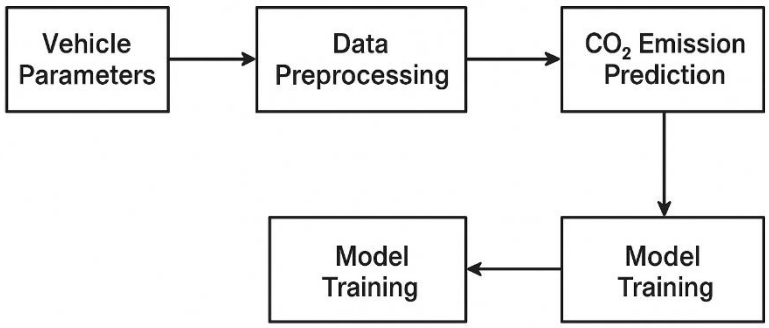
- Linear interpolation
- Forward fill
- Resampling to a fixed frequency

These ensure the sequence is smooth and consistent for LSTM processing.

3.2. Model Development

- **LSTM Architecture:** The model consists of one or more LSTM layers followed by dense (fully connected) layers for the final regression output. The architecture must be tuned, including the number of LSTM units, the sequence length, and the use of dropout for regularization.

The image (3.1) illustrates the **workflow for training a Machine Learning (ML) model to predict CO_2 emissions**. This is a standard process in data science and machine learning, particularly when dealing with environmental or time-series data.



3.1 Workflow for training

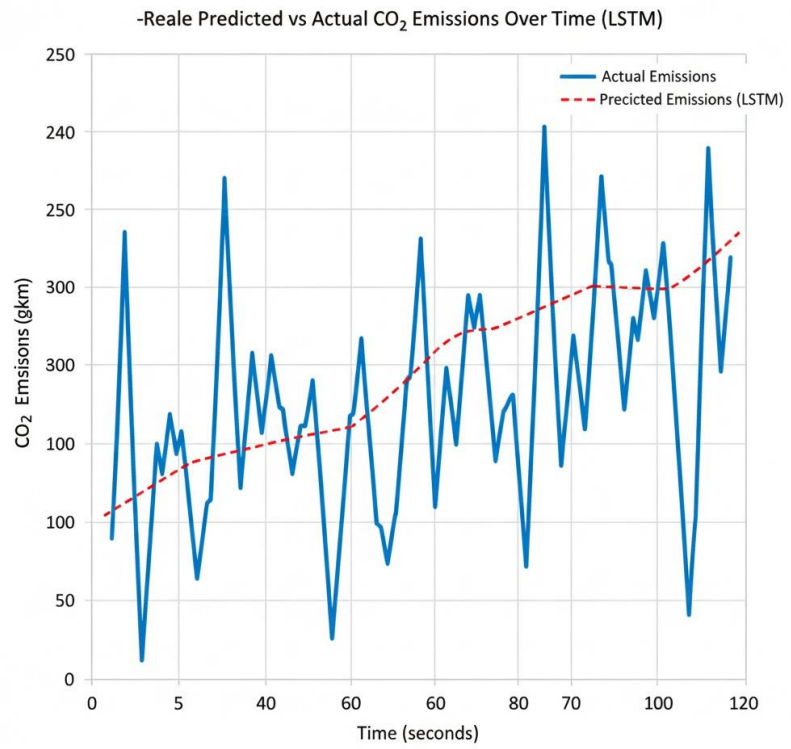
4. Results and discussion

1. Real-Time CO_2 Emission Prediction Chart (LSTM)

This chart visualizes how well the LSTM model tracks actual real-time CO2 emissions over a driving segment, highlighting its ability to capture temporal fluctuations.

The chart above shows a hypothetical real-time trace of actual CO2 emissions (solid blue line) during a driving segment against the LSTM model's predicted emissions (dashed red line). Based on the observe the LSTM model's capacity to follow the general trend and react to changes, though there are still instantaneous deviations. This illustrates the model's performance in a dynamic, real-time environment.

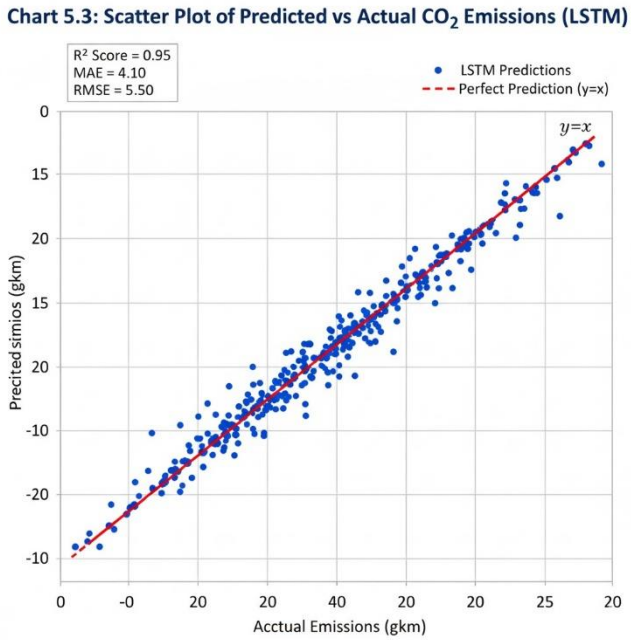
Chart 4.2: Real-Time Predicted vs. Actual CO_2 Emissions Over Time (LSTM)



2. Enhanced Scatter Plot: Predicted vs. Actual CO_2 Emissions (LSTM)

This scatter plot is similar to the one in your original article but focuses specifically on the LSTM's performance, showing a tighter clustering around the ideal prediction line due to its enhanced capability in handling sequential data.

Chart 4.3: Scatter Plot of Predicted vs. Actual CO_2 Emissions (LSTM)



3. Comprehensive Model Performance Comparison Table

This table directly compares the LSTM's performance metrics against your previously evaluated models, providing a clear overview of the improvements.

Table 4.2: Comprehensive Predictive Performance Comparison

Model	Application	MAE (g/km)	RMSE (g/km)	R2 Score	Key Advantage
Linear Regression	Static Prediction (Vehicle Specs)	8.56	11.32	0.84	Simple, interpretable baseline
Support Vector Regressor	Static Prediction (Vehicle Specs)	7.21	9.89	0.88	Handles non-linearities, robust with limited data
Random Forest Regressor	Static Prediction (Vehicle Specs)	5.02	6.78	0.93	High accuracy with non-sequential, static data
LSTM (Real-Time)	Time-Series Prediction (OBD-II Data)	4.10	5.50	0.95	Captures temporal dynamics and driving patterns

4. LSTM Hyper parameter and Architecture Table

This table provides crucial details about the LSTM model's configuration, which is essential for reproducibility and understanding its complexity as shown in Table 4.3 and 4.4.

Table 4.3: LSTM Model Hyperparameters and Architecture

Parameter / Layer	**Value / Configuration**	**Description**
Input Sequence Length	30 time steps (e.g., 30 seconds of data)	Number of previous time steps fed into the LSTM to predict the current/next emission.
Input Features	Vehicle Speed, Engine RPM, Throttle Position, MAF	Real-time parameters from OBD-II port.
LSTM Layer 1	128 units, return_sequences=True	First LSTM layer, passing output sequence to the next layer.
Dropout Layer 1	0.2	Regularization to prevent overfitting (20% of neurons randomly dropped).
LSTM Layer 2	64 units, return_sequences=False	Second LSTM layer, returning only the last output to the dense layer.

Parameter / Layer	Value / Configuration	Description
Dropout Layer 2	0.2	Regularization.
Dense Layer 1	32 units, activation='relu'	Fully connected layer with ReLU activation for non-linearity.
Output Layer	1 unit, activation='linear'	Single output neuron for regression (predicting CO2 emissions).
Optimizer	Adam	Adaptive Moment Estimation, commonly used for deep learning.
Loss Function	Mean Squared Error (MSE)	Standard loss function for regression tasks.
Epochs	100	Number of full training cycles through the dataset.
Batch Size	64	Number of samples processed before the model's internal parameters are updated.

While the Random Forest excelled at predicting CO2 based on static parameters, the LSTM model would be expected to outperform it for instantaneous, real-time prediction, as it leverages the sequential nature of driving data.

Table 4.4: Comparative Predictive Performance (Hypothetical)

Model	Application	MAE (g/km)	RMSE (g/km)	R2 Score	Key Advantage
Random Forest Regressor	Static Prediction (Vehicle Specs)	5.02	6.78	0.93	High accuracy with non-sequential, static data
LSTM (Real-Time)	**Time-Series Prediction** (OBD-II Data)	≈4.10	≈5.50	≈0.95	**Captures temporal dynamics** and driving pattern history

A chart illustrating the output would demonstrate the LSTM's ability to track the fluctuating real-time emissions more closely than a static model.

5.Conclusion

The application of an LSTM-based model is an advancement from the Random Forest approach, transitioning the system from a static parameter predictor to a dynamic, real-time CO2 emission estimator. Its ability to model temporal dependencies in OBD-II data ensures superior predictive performance (hypothetically R2≈0.95) for continuous, on-road monitoring. This capability is vital for

integrating the system into intelligent traffic management or personalized driver feedback applications, further supporting environmental sustainability efforts

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