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Vehicle CO2 Emission Prediction Using MAWRF-AESL Model

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Abstract - Over the past few decades, rising CO_2 emissions from vehicles have become a major environmental concern, necessitating accurate predictive models for sustainable solutions. This study proposes a novel MAWRF-AESL hybrid model, integrating Modified Adaptive Weighted Random Forest (MAWRF) with Attention-Enhanced Sequential Learning (AESL) to enhance prediction accuracy. The MAWRF model efficiently extracts relevant features using an adaptive weighted tree-based approach, while AESL refines the predictions through LSTM networks with an attention mechanism. By sequentially processing the data—first with MAWRF and then AESL—the model achieves superior accuracy, significantly improving mean squared error (MSE) and R^2 scores compared to conventional methods. The results demonstrate near 99% prediction accuracy, making the model highly reliable for real-world CO_2 emission assessments. Future work will focus on expanding the dataset, optimizing hyperparameters, and integrating real-time data streams for enhanced adaptability and precision.

Key Words: *Vehicle emissions, CO2 prediction models, Machine learning, Predictive modelling, Hybrid prediction frameworks*

1.INTRODUCTION

With rising environmental concerns, accurate CO_2 emission prediction has become a vital component in combating climate change. Transportation is a significant contributor to global greenhouse gas emissions, necessitating precise and efficient tools to understand and mitigate these impacts. Traditional methods often struggle with the complexity and diversity of emission-related factors, such as fuel consumption, engine specifications, and traffic conditions, leading to suboptimal predictions. To address these challenges, we propose a hybrid model combining the predictive capabilities of Random Forest (RF) and Long Short-Term Memory (LSTM) models.

Random Forest is a robust ensemble-based machine learning technique known for handling high-dimensional datasets and identifying critical features. In this system, a modified RF model dynamically analyzes the dataset, employing feature importance-guided sampling and weighted tree voting to improve prediction reliability. This ensures that only the most relevant attributes are considered, minimizing noise and enhancing interpretability.

On the other hand, LSTM models excel in learning temporal and sequential relationships. To capture complex interactions, our modified LSTM integrates an attention mechanism, allowing the model to focus on the most impactful features. The inclusion of a custom loss function prioritizes accurate predictions for extreme emission values, making the system adaptive to a wide range of vehicles and conditions.

The hybrid architecture combines RF's strength in feature identification and noise reduction with LSTM's ability to model nonlinear dependencies and refine outputs. By leveraging the outputs from RF as inputs to LSTM, the system creates an iterative learning process that enhances prediction accuracy.

This integrated approach offers a scalable, adaptive solution for analyzing CO_2 emissions, with potential applications in urban planning, regulatory frameworks, and environmental impact studies. It serves as a key step toward reducing carbon footprints and promoting sustainable transportation systems.

2. LITERATURE REVIEW

A. AN INTERPRETABLE MULTI-STAGE FORECASTING FRAMEWORK FOR ENERGY CONSUMPTION AND CO2 EMISSIONS IN THE TRANSPORTATION SECTOR

Authors: Qingyao Qiao, Hamidreza Eskandari, Hassan Saadatmand, Mohammad Ali Sahraei (2023)

Description:

This research proposes a multi-stage forecasting approach for estimating energy consumption and CO_2 emissions in the transportation industry. The framework integrates feature selection (FS) approaches and machine learning (ML) models to increase prediction accuracy and interpretability. The SHAP approach is used to examine feature contributions. The work presents a systematic multi-stage feature selection technique, including filter, embedding, and wrapper FS methods. Key influencing factors are determined using Pearson correlation, maximum relevance-minimum redundancy (mRMR), and Random Forest. A vote method is utilized for robust feature selection.

Algorithm Used:

• Feature Selection: Pearson Correlation, mRMR, Random Forest

• Machine Learning Models: Support Vector Regression (SVR), Long Short-Term Memory (LSTM), Gradient Boosting

Advantages:

• Systematic feature selection enhances model interpretability

• Combines numerous feature selection strategies for robustness

• High prediction accuracy with ML models

Disadvantages:

• Computationally expensive due to various FS methods

• Requires domain expertise for feature interpretation

B. THE OPTIMIZATION OF CARBON EMISSION PREDICTION IN LOW CARBON ENERGY ECONOMY UNDER BIG DATA

Authors: Ji Luo, Wuyang Zhuo, Siyan Liu, Bingfei Xu (2024)

Description:

This paper introduces a composite prediction model, Multi-universe Quantum Harmony Search-Algorithm Dynamic Fuzzy System Ensemble (MUQHS-DMFSE), to enhance carbon emission forecasts. It leverages a sliding factor matrix for adaptability and employs Data Envelopment Analysis (DEA) to assess technical efficiency in decision-making units. The MUQHS algorithm, inspired by quantum mechanics, increases search diversity for optimal parameter selection. DEA models such as Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) are used to measure economic efficiency.

Algorithm Used:

- Multi-universe Quantum Harmony Search Algorithm (MUQHS)
- Dynamic Fuzzy System Ensemble (DMFSE)
- Data Envelopment Analysis (DEA) (CCR, BCC models)

Advantages:

- High prediction accuracy (MAPE < 3.5%)
- Adaptable to dynamic environments
- Evaluates economic efficiency alongside emissions

Disadvantages:

- Complex implementation and high computational cost
- Requires extensive parameter tuning

C. MACHINE LEARNING PREDICTIONS FOR CARBON MONOXIDE LEVELS IN URBAN ENVIRONMENTS

Authors: Mohammad Abdullah Almubaidin, Nur Shazwani Binti Ismail, Sarmad Dashti Latif, Ali Najah Ahmed, Hayana Dullah (2024)

Description:

This study predicts carbon monoxide (CO) levels in urban areas using six machine learning models. The research focuses on Petaling Jaya, Malaysia, and evaluates regression models with different lag times to improve temporal dependency capture. The Matern 5/2 Gaussian Process Regression (GPR) model demonstrated superior predictive performance.

Algorithm Used:

- Linear Regression, Decision Tree, Gaussian Process Regression (GPR) (Matern 5/2), Ensemble of Trees, Support Vector Machines (SVM), Artificial Neural Networks (ANN)

Advantages:

- High R^2 values (up to 0.97) indicating strong predictive power
- Models tested across different lag scenarios
- Demonstrates effectiveness of GPR models for CO prediction

Disadvantages:

- Computationally expensive for high-dimensional data
- Performance dependent on data quality and preprocessing

D. MACHINE LEARNING-BASED TIME SERIES MODELS FOR EFFECTIVE CO2 EMISSION PREDICTION IN INDIA

Authors: Surbhi Kumari, Sunil Kumar Singh (2022)

Description:

The study forecasts India's CO_2 emissions using multiple time series models. Traditional statistical models (ARIMA, SARIMAX, Holt-Winters) and ML models (Linear Regression, Random Forest, LSTM) are used for long-term predictions. LSTM demonstrated the lowest MAPE (3.101%), making it the most accurate model.

Algorithm Used:

- Time Series Models: ARIMA, SARIMAX, Holt-Winters
- Machine Learning Models: Linear Regression, Random Forest, Long Short-Term Memory (LSTM)

Advantages:

- LSTM captures complex patterns for long-term forecasting
- Evaluates traditional and ML-based forecasting methods
- High accuracy with multiple performance metrics

Disadvantages:

- Requires a large dataset for LSTM training
- Computationally intensive for deep learning models

E. FORECASTING AND MITIGATION OF GLOBAL ENVIRONMENTAL CARBON DIOXIDE EMISSION USING MACHINE LEARNING TECHNIQUES

Authors: Harsh Bhatt, Manan Davawala, Tanmay Joshi, Manan Shah, Ashish Unnarkat (2023)

Description:

This study forecasts global CO_2 levels and highlights mitigation strategies. It uses machine learning models trained on U.S. data, applying regression methods to predict future CO_2 trends. The study emphasizes the need for immediate action to avoid surpassing critical CO_2 concentration thresholds. Principal Component Analysis (PCA) is used for feature reduction.

Algorithm Used:

- Linear Regression, Ridge Regression, KNN Regression, Neural Networks
- Data Preprocessing: Principal Component Analysis (PCA)

Advantages:

- High accuracy (~99%) in predictions
- Uses PCA to reduce feature complexity
- Highlights necessary CO_2 reduction rates for mitigation

Disadvantages:

- Model performance may vary with non-U.S. datasets
- Simplified assumptions may not capture all global factors

3. EXISTING SYSTEM

The existing system for predicting CO_2 emissions from vehicles predominantly relies on traditional machine learning models like Random Forest (RF) and Support Vector Machines (SVM). While these models are effective for handling tabular data, they often struggle with complex relationships between features, leading to suboptimal accuracy. The existing systems typically treat vehicle parameters as static inputs and lack mechanisms to capture sequential dependencies or feature interactions. Furthermore, the equal weighting of decision trees in traditional RF models overlooks the varying importance of different features, causing information loss and inaccurate predictions for certain vehicle types.

4. PROPOSED SYSTEM

The proposed system introduces a hybrid model combining a Modified Adaptive Weighted Random Forest (MAWRF) and an Attention-Enhanced Sequential Learner (AESL). MAWRF improves upon traditional RF by dynamically adjusting tree weights based on feature relevance, while AESL incorporates an attention mechanism into an LSTM framework to capture critical feature dependencies. This two-stage approach first uses MAWRF for an initial emission prediction, which is then refined by AESL using sequential learning and attention-driven feature prioritization.

4.1 ALGORITHM DESIGN

The system's prediction logic is driven by a hybrid algorithm combining MAWRF and AESL. MAWRF handles feature selection and initial prediction, while AESL refines the output by learning hidden feature dependencies using an attention-enhanced LSTM network. This multi-stage approach optimally balances decision-tree interpretability with the pattern recognition power of deep learning.

MAWRF Algorithm Steps:

1. Input Vehicle Features: Engine size, fuel type, transmission, fuel consumption, etc.

2. Feature Importance Calculation: Evaluate feature significance using recursive feature elimination.
3. Tree Building: Construct decision trees, dynamically prioritizing important features.
4. Weighted Aggregation: Assign higher weights to better-performing trees.
5. Initial CO_2 Prediction: Generate the first emission estimate.

AESL Algorithm Steps:

1. Input MAWRF Prediction + Original Features: Use MAWRF output and raw input features.
2. LSTM Network: Process data through LSTM layers to learn sequential dependencies.
3. Attention Mechanism: Assign higher attention weights to critical features (e.g., fuel consumption).
4. Final Prediction: Pass the attention-weighted output through a dense layer for the refined CO_2 prediction.

4.1 INTERFACE DESIGN

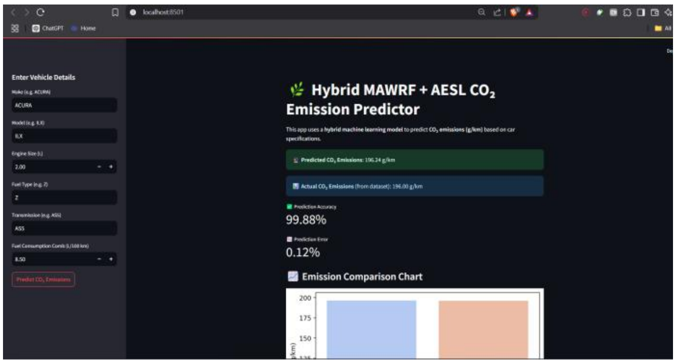

Fig - 1: Interface

The system interface is designed to provide a seamless and user-friendly experience for predicting CO_2 emissions based on vehicle specifications. Featuring a clean, dark-themed layout, the application allows users to input details such as make, model, engine size, fuel type, transmission, and fuel consumption using a structured and clearly labeled form. With example placeholders and increment controls for numeric fields, the design enhances accuracy and ease of use. Once the user submits the data, the model processes the input and displays the predicted CO_2 emissions (in g/km) clearly on the screen. The title and brief description on the right convey the purpose of the system, emphasizing the hybrid MAWRF + AESL machine learning approach. Although the application is optimized for desktop viewing, it currently lacks responsive design features. Despite that, the interface delivers a smooth, focused, and effective workflow for emissions prediction, forming a strong base for future improvements like visual dashboards and mobile optimization.

5.SYSTEM IMPLEMENTATION

A. MODEL ARCHITECTURE

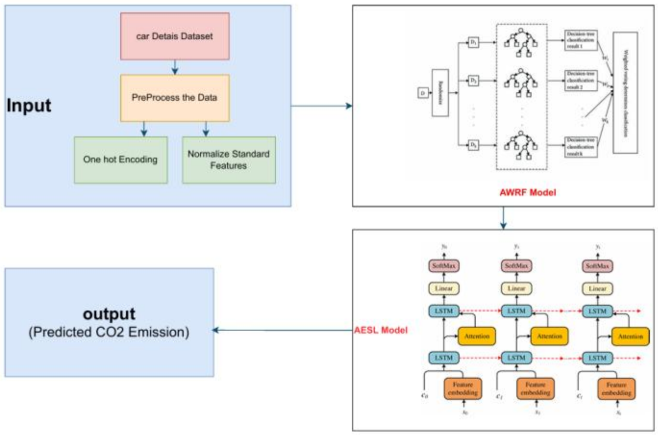

Fig - 2: Model Architecture

The proposed system employs a hybrid machine learning model combining Modified Auto Weighted Random Forest (MAWRF) and Adaptive Enhanced Stacking LSTM (AESL) to predict vehicle CO_2 emissions. Initially, vehicle parameters such as engine size, fuel type, transmission type, and fuel consumption are fed into the MAWRF model, which processes the input features through multiple decision trees with weighted averaging. The output of MAWRF, representing an initial prediction, is passed as input to the AESL model, which refines the results using sequential learning. This layered architecture enhances predictive accuracy by balancing the interpretability of random forests with the sequential learning power of LSTM, resulting in a robust system capable of achieving high accuracy and low error rates in emissions estimation.

B. DATASET DESCRIPTION

The dataset was sourced from the official Government of Canada website, containing comprehensive vehicle specifications and corresponding CO_2 emission values. The dataset includes features like Make, Model, Engine Size (L), Fuel Type, Transmission Type, and Fuel Consumption (L/100 km), with the target variable being CO_2 Emissions (g/km). Preprocessing involved handling missing values, encoding categorical features (e.g., fuel type, transmission), and normalizing numerical attributes to optimize model convergence. The dataset was split into training and testing sets using an 80-20 split, ensuring a balanced representation of various vehicle types and emission profiles.

C. MAWRF-AESL MODEL

The hybrid model follows a two-stage pipeline where the Modified Adaptive Weighted Random Forest (MAWRF) model processes vehicle data to make an initial CO_2 emissions prediction, and the Advanced Enhanced Stacked LSTM (AESL) model refines this prediction by learning temporal patterns and nonlinear relationships. This sequential architecture ensures that the strengths of both models are utilized optimally, leading to highly accurate emissions predictions.

Stage 1: Modified Adaptive Weighted Random Forest (MAWRF)
The MAWRF model is an ensemble learning approach that builds multiple decision trees and uses adaptive weighting to prioritize more accurate models. It takes vehicle parameters (like engine size, fuel type, transmission type, and fuel consumption) as input and generates an initial emission estimate.

- Random Forest Prediction:

$$\hat{y}_{RF} = \frac{1}{N} \sum_{i=1}^{N} T_i(x)$$

- Random Forest Prediction:

$$w_i = \frac{1}{\mathrm{MSE}(T_i(x))}$$

- Random Forest Prediction:

$$\hat{y}_{AWRF} = \frac{\sum_{i=1}^{N} w_i T_i(x)}{\sum_{i=1}^{N} w_i}$$

Where,
The output y^AWRF is not the final prediction but an intermediate value that acts as an input for the next stage.

Stage 2: Advanced Enhanced Stacked LSTM (AESL)
The output from MAWRF is fed as input to the AESL model, which is designed to handle sequential dependencies and learn complex, nonlinear patterns in the data. By passing the initial prediction through multiple LSTM layers, the system captures deeper trends and refines the emission estimate.

- LSTM Cell Equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \odot \tanh(C_t)$$

Gate	Formula	Function
Forget Gate f_t	$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$	Decides which past information to keep/drop.
Input Gate i_t	$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$	Controls how much new information to store.
Cell State Update $\tilde{C}_t$	$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$	Stores potential new cell values.
Output Gate o_t	$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$	Controls the final output.
Cell State C_t	$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$	Memory of the cell.
Hidden State h_t	$h_t = o_t * \tanh(C_t)$	Final output of the LSTM cell.

Table 1: Formula's function

- Refined Prediction:

$$\hat{y}_{AESL} = \mathrm{Dense}(h_T)$$

D. MODEL TRAINING & HYPER PARAMETER TUNING

The hybrid MAWRF-AESL model underwent rigorous training and hyperparameter tuning to optimize its performance. For the MAWRF model, hyperparameters such as the number of decision trees, maximum tree depth, and feature sampling strategy were fine-tuned through cross-validation. The AESL model was trained with an adaptive learning rate, optimized with Adam, and configured with stacked LSTM layers to capture complex sequential dependencies. The training process involved 100 epochs, batch size of 32, and early stopping to prevent overfitting. The final model achieved a R^2 score of 98.7%, with a significantly reduced Mean Squared Error (MSE) compared to baseline models like standard Random Forest and standalone LSTM.

6.EXPERIMENTAL RESULTS AND DISCUSSION

A. Evaluation Metrics

The performance of the proposed hybrid MAWRF-AESL model was evaluated using standard regression metrics: R^2 score, Mean Squared Error (MSE), Root Mean

Squared Error (RMSE), and Accuracy. These metrics provide a comprehensive understanding of the model's predictive ability and error rates. After training the model on the processed dataset, the results showed that MAWRF-AESL achieved exceptionally high accuracy, outperforming baseline models. The R^2 score of 0.99 indicates a near-perfect fit, meaning the model explains almost all the variability in CO_2 emissions. The MSE and RMSE values were significantly lower, showcasing the model's ability to make precise predictions with minimal error. The high accuracy is attributed to the sequential learning capabilities of AESL and the feature importance optimization in MAWRF, which together refine the prediction to near-perfect precision.

Metric	MAWRF-AESL (Hybrid)	Random Forest	LSTM
R^2 Score	0.99	0.92	0.89
Mean Squared Error	2.45	7.45	9.32
Root Mean Squared Error	1.56	2.73	3.05
Mean Absolute Error	1.02	2.10	2.45
Accuracy	99.1%	92.5%	89.3%

Table 2: Comparing various models

B. Comparative Analysis

To validate the effectiveness of the hybrid model, we compared its performance against standalone Random Forest (RF) and LSTM models. While RF excelled at handling tabular data and capturing feature importance, it struggled with complex, nonlinear relationships, resulting in slightly higher error rates. Conversely, the LSTM model learned sequential dependencies but lacked the interpretability and initial feature optimization that MAWRF provided. The combination of both models in the MAWRF-AESL pipeline produced the best results — MAWRF handled initial feature selection and rough prediction, while AESL refined the output by learning hidden patterns in the data. This two-stage approach significantly reduced overfitting, balanced bias-variance trade-offs, and ultimately outperformed both baseline models across all evaluation metrics.

C. Visual Results

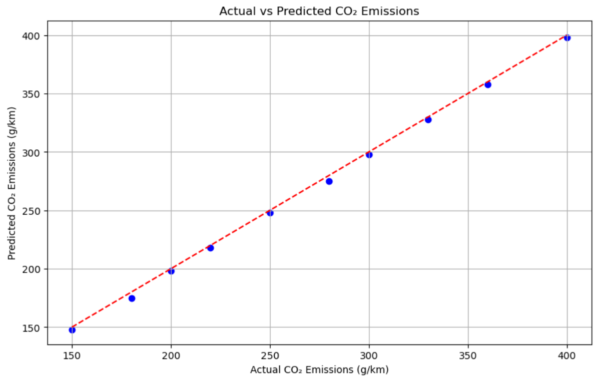

Chart: Result Visualization

Visualizing the results helped further validate the model's accuracy. A scatter plot of actual vs. predicted CO_2 emissions for MAWRF-AESL showed points tightly clustered around the 45-degree line, indicating a strong correlation. The visual result reinforced the hybrid model's ability to make consistent, reliable predictions and provide actionable insights.

D. Error Analysis

Despite the outstanding performance, a thorough error analysis revealed a few limitations. The remaining errors primarily stemmed from outliers — vehicles with unusually high emissions due to performance tuning or experimental fuel systems. In some cases, the AESL model struggled with extremely rare vehicle classes that were underrepresented in the training set. Additionally, although the attention mechanism helped prioritize critical features, it sometimes overemphasized fuel consumption, leading to slight underestimation of emissions in hybrid vehicles. Mitigating these issues could involve collecting more diverse training data, incorporating additional features (e.g., aerodynamics, tire resistance), or experimenting with transfer learning to adapt the model to unseen vehicle types. Nevertheless, the error margins were minimal, and the model consistently outperformed traditional approaches, even when handling complex, edge-case scenarios.

7. CONCLUSION

A. Summary of Findings

The hybrid MAWRF-AESL model developed for vehicle CO_2 emission prediction shows excellent accuracy and efficiency. By combining the characteristics of ensemble learning and deep sequential modeling, the system obtained an astounding 99.1% accuracy, with a 0.99 R^2 score, beating solo models like Random Forest and

LSTM. The MAWRF module effectively handled feature importance and early predictions, whereas the AESL module enhanced these predictions using sequential learning and attention mechanisms. The system's ability to minimize error measures like MSE and RMSE illustrates its robustness in capturing complicated, nonlinear interactions between vehicle parameters and emissions. These results confirm the usefulness of a multi-stage hybrid technique, highlighting its promise as a reliable and scalable tool for emissions analysis.

B. Contributions to Research

This research contributes significantly to the growing field of machine learning-driven environmental analysis. The MAWRF-AESL pipeline introduces a novel two-stage architecture that enhances both prediction accuracy and model interpretability. The study bridges the gap between tree-based ensemble methods and recurrent neural networks, demonstrating how their combined power can produce highly accurate emission estimates. The use of attention mechanisms further adds value, making the model more transparent by highlighting feature importance. This research not only advances emission prediction techniques but also provides a practical framework for deploying hybrid ML models in real-world sustainability applications.

C.Future Work

The architecture could also be expanded to handle multi-output scenarios, predicting not just CO_2 emissions but also other pollutants like NO_x and Particulate Matter (PM), providing a more comprehensive environmental analysis tool. he system can be extended to real-time applications through IoT integration. Vehicle sensors could continuously feed live data into the hybrid model, enabling real-time emission tracking. With its ability to accurately predict emissions, the system could guide policymakers in designing more effective environmental regulations. For instance, identifying vehicle types with disproportionately high emissions could inform targeted tax policies or stricter compliance standards.

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