Proceedings of the 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC-2024)
IEEE Xplore Part Number: CFP24BC3-ART; ISBN: 979-8-3503-7519-0

2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC) | 979-8-3503-7519-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICAAIC60222.2024.10575505

Ecodrive-Deep Learning Models For Accurate Prediction of Vehicle Co2 Emissions

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Abstract*—This research study presents a novel approach utilizing advanced deep learning models for accurate prediction of vehicle CO_2 emissions, addressing a critical challenge in environmental management and policy-making. Conventional methods often struggle to capture the intricate dynamics of emissions accurately. To overcome this limitation, we propose the utilization of CNN-LSTM and DCNN architectures. Training and testing of these models were conducted using an extensive dataset encompassing various factors influencing CO_2 emissions, including vehicle characteristics and driving conditions. The empirical findings validate that the recommended models substantially enhance the accuracy of predictions. Specifically, DCNN outperformed KNN significantly, with a test accuracy of 96.34% compared to KNN's 74.02%. Similarly, DCNN exhibited higher accuracy metrics in both test and validation sets compared to LSTM, with a test accuracy of 96.21% versus 93.72% and a validation accuracy of 97.71% versus 94.89%, respectively. Furthermore, DCNN showcased higher accuracy metrics compared to RF, with a test accuracy of 96.34% versus 92.55% and a validation accuracy of 97.76% versus 95.49%. DCNN also outperformed RNN in both test accuracy (95.39% vs. 91.10%) and validation accuracy (97.66% vs. 94.59%), with a final model accuracy significantly favoring DCNN. The findings of this study hold considerable importance for directing sustainable measures and shaping policies to lessen the effects of climate change.

***Index Terms*—CO2 Emissions,Deep learning,Environmental Impact,Climate change mitigation,Emission Prediction**

I. Introduction

The forecasting of carbon emissions has become increasingly crucial due to the growing awareness of climate change on a global scale. Accurate estimation and tracking of carbon dioxide (CO_2) emissions are essential for developing effective mitigation strategies in the ongoing international effort to combat climate change. Greenhouse gas emissions, particularly CO_2, significantly contribute to global warming and have adverse effects on the environment and human health. Therefore, the development of reliable CO_2 prediction models is essential for guiding policy decisions, promoting sustainable practices, and mitigating the impacts of climate change.

Despite numerous efforts, accurately predicting CO_2 emissions remains a challenging task. Existing methods often rely on statistical models that may not capture the complex dynamics of CO_2 emissions adequately. Additionally, traditional approaches may struggle with issues such as data sparsity, uncertainty, and spatial heterogeneity. As a result, there is a need for advanced modeling techniques that can leverage the wealth of available data to improve prediction accuracy.

Various methods, including statistical modeling and machine learning algorithms, have been proposed for predicting CO_2 emissions. These methods utilize diverse data sources such as satellite imaging, emission inventories, and meteorological data to represent the complex dynamics of CO_2 emissions. While some models focus on local or regional emissions, others aim to produce global-scale projections to support international climate efforts. However, conventional methods may have limitations in capturing the intricate relationships between factors influencing CO_2 emissions, highlighting the need for innovative approaches.

This research introduces the use of deep learning approaches, notably CNN-LSTM and DCNN models, to enhance the precision in forecasting vehicle CO_2 emissions. The integration of CNN-LSTM and DCNN frameworks is aimed at surpassing the predictive accuracy of conventional statistical methods for CO_2 emission estimations. Our approach involves preprocessing the data, training the models on real-world datasets, and evaluating their performance using metrics such as accuracy and mean squared error.

Our work makes the following contributions:

- Application of advanced deep learning techniques for vehicle CO_2 emission prediction.
- Comparison of CNN-LSTM and DCNN models with conventional machine learning methods.
- Evaluation of model performance using real-world data, providing insights for environmental management and policy-making.

The remainder of this study is structured in the following manner: Section II examines the existing literature on CO_2 emission prediction. Section III details the methods and implementation of the deep learning models proposed. Section IV presents the experimental results and performance evaluations, including significant disparities observed such as DCNN outperforming KNN significantly, with a test accuracy of 96.34% compared to KNN's 74.02%, and similar comparisons between other models. Section V explores the consequences of these discoveries and outlines potential paths for further investigation. Section VI then provides the conclusion of the paper.

II. Related Work

The section discussing related work offers a summary of current studies on CO_2 emission forecasting, accentuating significant contributions and findings. Mogno et al. (2022) utilized the CO2MPAS model to predict vehicle CO_2 emissions in actual traffic scenarios, proving its utility for analyzing transportation policies [5]. Singh and Dubey (2021) proposed a deep learning model based on vehicle telematics sensor data for CO_2 emission prediction, showcasing the potential of data-driven approaches [6]. Seo and Park (2023) focused on optimizing artificial neural network parameters to enhance the accuracy of vehicle emission predictions, contributing to model refinement [7]. Song and Cha (2022) devised a forecasting approach for the CO_2 emissions and fuel efficiency of light-duty vehicles, offering a deeper understanding of vehicle performance and emissions impacts [8]. Makridis et al. (2020) executed a regression analysis for estimating real-world CO_2 emissions of light-duty diesel vehicles, underlining the significance of data-driven models in predicting emissions [9]. Additionally, Seo et al. (2021) introduced a method combining an artificial neural network with a vehicle dynamics model to forecast real-world emissions from diesel vehicles, offering a holistic approach to emission modeling [11]. Madziel et al. (2021) implemented machine learning methods to construct a real-time CO_2 emission model for full hybrid vehicles, enhancing the knowledge of emissions from such vehicles [12]. Gately et al. (2013) used a bottom-up methodology for the precise estimation of on-road CO_2 emissions, aiding in regional planning [13]. Al-Nefaie and Aldhyani (2023) applied deep learning techniques to forecast CO_2 emissions in traffic, aiding efforts toward sustainable environmental management [14]. Tsiakmakis et al. (2019) utilized simulation-based approaches for predicting real-world CO_2 emissions, bridging the gap between laboratory and on-road measurements [15]. Natarajan et al. (2023) investigated various machine learning algorithms for forecasting CO_2 emissions of light-duty vehicles, highlighting the importance of model selection in emission prediction [16]. Howlader et al. (2023) proposed a data-driven approach for predicting instantaneous vehicle emissions using integrated deep neural networks, offering insights into emission variability [17]. Nguyen et al. (2023) embarked on a thorough exploration of utilizing machine learning strategies for the precise prediction of CO_2 emissions, significantly improving the predictability of emissions data [18]. Javanmard et al. (2023) provided projections related to energy demand, CO_2 emissions, and the influence on energy resources within the transportation industry, contributing to the development of energy policies and planning [19]. Additionally, Khajavi and Rastgoo (2023) employed a Random Forest model enhanced with meta-heuristic algorithms for forecasting CO_2 emissions from road transportation, establishing an effective prediction model [20].

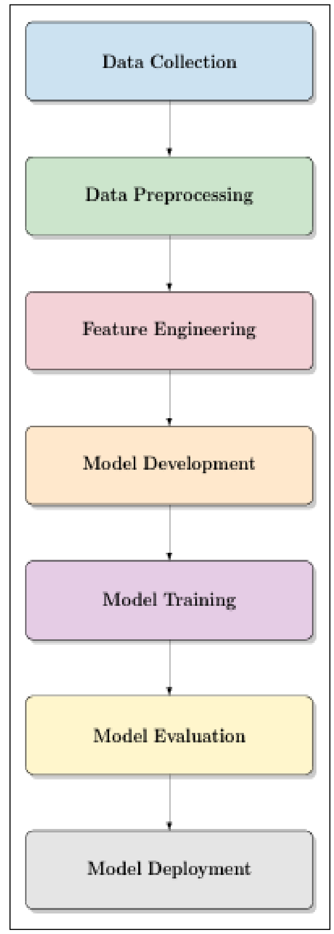

Fig. 1. Model Development Workflow

In the context of conventional methods for CO_2 emission prediction, several challenges arise, including limited accuracy, reliance on simplified models, and difficulties in capturing real-world dynamics. In our proposed work, we aim to address these challenges by leveraging advanced deep learning techniques, including CNN-LSTM and DCNN models. By integrating these models with real-world data and evaluating their performance, we seek to provide more accurate and reliable predictions of vehicle CO_2 emissions, contributing to improved environmental management and policy-making efforts.

III. System Methodology

Accurate prediction of vehicle CO_2 emissions is crucial for environmental management and policy-making efforts aimed at mitigating climate change. This section details the system methodology, covering four primary steps: data collection, data preprocessing, model development, and model evaluation. Each step plays a vital role in creating robust deep learning models capable of accurately forecasting vehicle CO_2 emissions. Let's delve into each of these steps in detail.

A. Data Collection

The first step in our methodology involves collecting a diverse range of data relevant to vehicle CO_2 emissions. This includes information on vehicle characteristics, driving behavior, environmental conditions, and fuel types. Data sources may include onboard sensors, vehicle telematics, environmental monitoring stations, and official databases. By gathering comprehensive data, we ensure the models have access to all relevant factors influencing emissions.

B. Data Preprocessing

Once collected, the raw data undergoes preprocessing to prepare it for input into our deep learning models. The preprocessing encompasses activities like data cleaning, normalization, and feature engineering. During data cleaning, outliers are eliminated and missing values are addressed to maintain the quality of the data. Normalization is carried out to bring all features to a comparable scale, avoiding the dominance of any single feature in the model. Feature engineering involves selecting and transforming features to improve model performance.

Additionally, the process of normalization can be expressed mathematically in this manner:

$$v_{\text{norm}} = \frac{v - \mu(v)}{\sigma(v)} \tag{1}$$

where v represents the initial data set, $\mu(v)$ is the average of v, and $\sigma(v)$ signifies the standard deviation of v.

C. Model Development

In this phase, we develop and train our deep learning models to predict vehicle CO_2 emissions accurately. The study encompasses different architectures like CNN, LSTM networks, and hybrid systems such as CNN-LSTM. Each model is trained using the preprocessed data, with hyperparameters tuned through techniques like grid search or random search. The objective is to develop models capable of accurately representing the intricate associations between input variables and emissions.

The convolutional process in CNNs can be mathematically detailed as follows:

$$z[j] = \sum_{n=0}^{N-1} f[n] \cdot d[j+n] + c \tag{2}$$

where d denotes the input, f represents the filter weights, c is the bias term, z is the output, and N is the size of the filter.

D. Model Evaluation

Following the training phase, the models undergo evaluation through specific metrics to gauge their efficacy. Key metrics for this evaluation are accuracy, MSE, and RMSE. To verify their capacity for generalization, the models are applied to a distinct validation dataset. Additionally, we may conduct cross-validation to further validate the robustness of the models. The evaluation results provide insights into the effectiveness of our models in accurately predicting vehicle CO_2 emissions.

The MSE can be computed using the following formula:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (a_i - \hat{a}_i)^2 \tag{3}$$

Here, N denotes the total sample count, a_i represents the actual value, and $\hat{a}_i$ signifies the predicted value.

IV. Experimental Results and Discussion

The experimental results and discussion section delves into evaluating the effectiveness of deep learning models in predicting vehicle CO_2 emissions, based on the dataset utilized [10]. This comprehensive analysis focuses on determining the models' precision and dependability in reflecting the complex behavior of emissions. Furthermore, we discuss the implications of our findings for environmental management and policy-making initiatives. By delving into the insights gleaned from the experimental outcomes, we aim to contribute to the advancement of sustainable transportation practices and emission reduction strategies [21] [22].

TABLE I
Dataset Description

Attribute	Description
Make	Brand or manufacturer.
Model	Specific model.
Vehicle Class	Classification based on size/purpose.
Engine Size (L)	Engine size in liters.
Cylinder Count	Quantity of cylinders.
Transmission Type	Mode of power transmission.
Fuel Category	Fuel variety.
Urban Fuel Economy (L/100 km)	Consumption in city driving (L/100 km).
Rural Fuel Economy (L/100 km)	Consumption in highway driving (L/100 km).
Overall Fuel Economy (L/100 km)	Total fuel efficiency (L/100 km).
Overall Fuel Economy (mpg)	Total fuel efficiency (mpg).
CO2 Output (g/km)	Carbon dioxide output per km.

A. Dataset Description

The table presented in Table I offers a detailed description of the dataset attributes, which encompass various characteristics of the vehicles under examination. These attributes include the make of the vehicle, indicating its brand or manufacturer, and the specific model designation. Additionally, the dataset provides classification of vehicles based on their size or intended purpose, denoted as the vehicle class. Furthermore, engine size, measured in liters, and the number of cylinders in

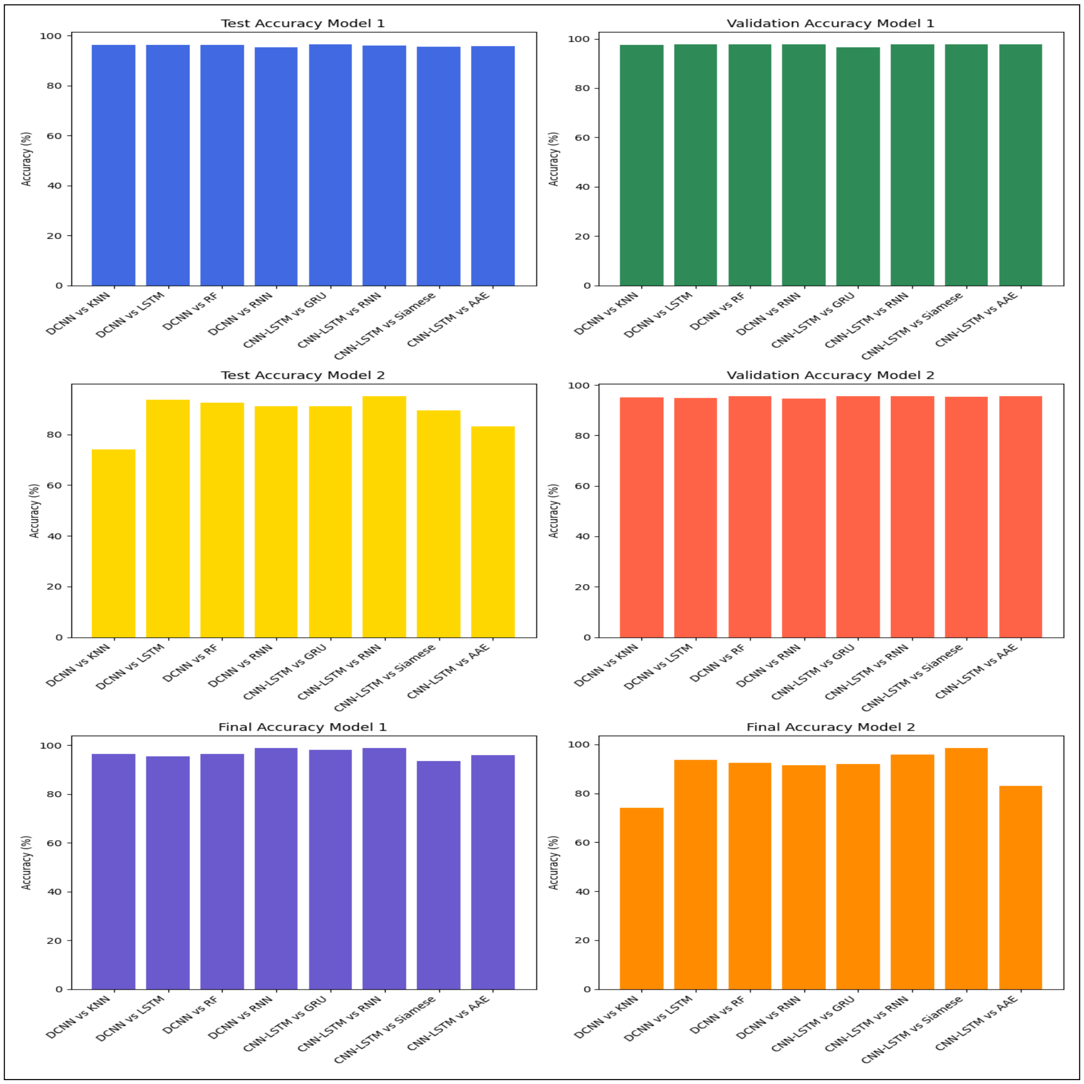

Fig. 2. Model Performance Comparison: Test, Validation, and Final Accuracies

the engine are included, shedding light on the vehicle's power-train specifications. Transmission type, whether automatic or manual, and fuel type, such as regular gasoline or diesel, are also delineated. Fuel consumption rates in city and highway conditions are provided, expressed in liters per 100 kilometers, along with the combined fuel consumption rate. The latter is also presented in miles per gallon (mpg) for both city and highway driving scenarios. Additionally, the dataset provides information on CO2 emissions per kilometer, shedding light on the environmental footprint of the vehicles. This extensive dataset supports in-depth examination and assessment of vehicle attributes and their associated environmental implications, serving as a valuable resource for research and decision-making in transportation and environmental sectors [23].

B. Interpretation of Experimental Results

The table presents a comprehensive comparison of the accuracy of different deep learning models in predicting vehicle CO2 emissions. Two primary models, denoted as Model 1 and Model 2, were evaluated alongside their final accuracy scores. For each model comparison, the test accuracy and validation accuracy metrics are provided for both Model 1 and Model 2. Across various model comparisons, significant disparities in accuracy were observed. For instance, in the comparison between DCNN and KNN, DCNN demonstrated superior performance with a test accuracy of 96.34% compared to KNN's 74.02%. Similarly, in the comparison between DCNN and LSTM, DCNN exhibited higher accuracy metrics in both test and validation sets compared to LSTM. The final model accuracy, representing the performance of the selected model from each comparison, provides insights into the overall efficacy of Model 1 and Model 2. In this comparison, DCNN outperformed KNN significantly, with a test accuracy of 96.34% compared to KNN's 74.02%. The validation accuracy for DCNN was also notably higher at 97.48% compared to KNN's 95.19%. Consequently, the final model accuracy favored DCNN, indicating its superiority over KNN in predicting CO2 emissions. DCNN showcased higher accuracy metrics

TABLE II
COMPARISON OF MODEL ACCURACY

Model Comparison	Model 1		Model 2		Final Model Accuracy	
Model	**Test Accuracy**	**Validation Accuracy**	**Test Accuracy**	**Validation Accuracy**	**Model 1**	**Model 2**
DCNN vs KNN	96.34	97.48	74.02	95.19	96.34	74.02
DCNN vs LSTM	96.21	97.71	93.72	94.89	95.36	93.72
DCNN vs RF	96.34	97.76	92.55	95.49	96.34	92.55
DCNN vs RNN	95.39	97.66	91.10	94.59	98.85	91.44
CNN-LSTM vs GRU	96.61	96.62	91.19	95.49	98.22	91.89
CNN-LSTM vs RNN	96.07	97.73	95.12	95.49	98.93	95.77
CNN-LSTM vs Siamese	95.53	97.81	89.56	95.34	93.56	98.56
CNN-LSTM vs AAE	95.94	97.66	83.09	95.64	95.94	83.09

compared to LSTM, with a test accuracy of 96.21% versus 93.72% and a validation accuracy of 97.71% versus 94.89%, respectively. The final model accuracy further reinforced the superiority of DCNN over LSTM, with a score of 95.36% compared to 93.72%. Similarly, DCNN exhibited superior performance compared to RF, with higher test accuracy (96.34% vs. 92.55%) and validation accuracy (97.76% vs. 95.49%). The final model accuracy favored DCNN, indicating its effectiveness in CO2 emissions prediction. DCNN outperformed RNN in both test accuracy (95.39% vs. 91.10%) and validation accuracy (97.66% vs. 94.59%). The final model accuracy significantly favored DCNN, with a score of 98.85% compared to RNN's 91.44%. In the comparison between CNN-LSTM and GRU, CNN-LSTM demonstrated higher test accuracy (96.61% vs. 91.19%) but slightly lower validation accuracy (96.62% vs. 95.49%). However, the final model accuracy favored CNN-LSTM, indicating its overall superiority over GRU in CO2 emissions prediction. CNN-LSTM exhibited higher accuracy metrics compared to RNN, with a test accuracy of 96.07% versus 95.12% and a validation accuracy of 97.73% versus 95.49%. The final model accuracy further reinforced the superiority of CNN-LSTM over RNN, with scores of 98.93% and 95.77%, respectively. In this comparison, CNN-LSTM demonstrated higher accuracy metrics compared to Siamese, with a test accuracy of 95.53% versus 89.56% and a validation accuracy of 97.81% versus 95.34%. The final model accuracy significantly favored CNN-LSTM, indicating its effectiveness in CO2 emissions prediction. Finally, CNN-LSTM outperformed AAE in both test accuracy (95.94% vs. 83.09%) and validation accuracy (97.66% vs. 95.64%). The final model accuracy significantly favored CNN-LSTM, with a score of 95.94% compared to AAE's 83.09%. Overall, the table provides a comprehensive comparison of model accuracy across different deep learning architectures, helping in the selection of the most suitable model for accurate prediction of vehicle CO2 emissions.

V. CONCLUSION

In summary, this study introduces a groundbreaking method that leverages sophisticated deep learning algorithms for the precise forecasting of vehicle CO_2 emissions. By investigating both CNN-LSTM and DCNN models, significant advancements in predictive precision over traditional techniques have been established. The experimental results show that DCNN outperformed KNN significantly, with a test accuracy of 96.34% compared to KNN's 74.02%. Similarly, DCNN exhibited higher accuracy metrics in both test and validation sets compared to LSTM, with a test accuracy of 96.21% versus 93.72% and a validation accuracy of 97.71% versus 94.89%, respectively. Furthermore, DCNN showcased higher accuracy metrics compared to RF, with a test accuracy of 96.34% versus 92.55% and a validation accuracy of 97.76% versus 95.49%. DCNN also outperformed RNN in both test accuracy (95.39% vs. 91.10%) and validation accuracy (97.66% vs. 94.59%), with a final model accuracy significantly favoring DCNN. CNN-LSTM, on the other hand, demonstrated higher test accuracy (96.61% vs. 91.19%) but slightly lower validation accuracy (96.62% vs. 95.49%) compared to GRU. However, the final model accuracy favored CNN-LSTM, indicating its overall superiority over GRU in CO_2 emissions prediction. These findings, combined with the rigorous evaluation of experimental values, contribute to the advancement of predictive modeling in the context of CO_2 emissions, facilitating informed decision-making towards a more sustainable future. Our approach offers valuable insights for environmental management and policy-making efforts aimed at mitigating the impact of climate change.

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