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Proactive Monitoring And Prediction Of Vehicle Exhaust Emissions For Enhanced Environmental Health

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Abstract: The Exhaust Emission Index (EEI) tells you how many air pollutants a vehicle releases and a higher number indicates that air quality is worse. The traditional PUC story is that it only tests your car's emissions at a single point, unlike the way dynamic health checks consider the car's overall status. As the number of vehicles on the road grows, it is more important than ever to have advanced systems to watch and predict emissions in real-time. This project introduces an innovative system called Emission Tracker that uses deep learning techniques called LSTM networks to fill this gap. An LSTM model on a central server is used by the Emission Tracker to monitor vehicle carbon emissions and estimate future trends for the Vehicle Exhaust Emission Index (VEEI). The system includes a web portal with an easy-to-understand design for looking at emissions data. With insights based on location, users can better understand how much carbon is being emitted which helps them decide how to act. You can check how emissions are changing today, as well as estimate their future trends using the Emission Tracker. Taking action ahead of problems means interventions can be put in place on time, helping the environment and the health of everyone.

Keywords: Carbon Emission Monitoring, Greenhouse Gas Tracking, IoT-based Environmental Monitoring, Carbon Footprint Estimation, Real-time Emission Analytics, Sustainable Technology Solutions, Artificial Intelligence in

Climate Action, Data-Driven Environmental Management, Mobile Application for Emission Tracking, Smart Environmental Monitoring System, Cloud-based Emission Reporting, Low-Carbon Lifestyle Assessment

INTRODUCTION

Carbon dioxide is released into the air every time the air-fuel mixture in internal combustion engines catches fire. Since all three types of vehicle, gasoline, diesel and hybrid- burn fuels with different hydrocarbon structures, vehicle exhaust emissions result. Fuel evaporation from inside the vehicle when it's resting or being filled adds to exhaust emissions. The composition of gases in vehicle exhaust is based on the operating characteristics of each car and the fuel it uses. Carbon dioxide, nitrogen, water vapor and oxygen in unspent air make up the majority of what comes out of a vehicle's exhaust. In addition to standard emissions, vehicle exhaust includes carbon monoxide, unburned fuel, nitrogen oxides and tiny amounts of mercury. Several of these compounds are important causes of air pollution from vehicles and carbon dioxide which is a greenhouse gas, contributes to climate change.

PROBLEM IDENTIFIED

Emissions from vehicles cause major problems such as air pollution, harm to health and harm to the environment. Due to its emissions of carbon monoxide, nitrogen oxides and particulate matter such transport leads to respiratory issues, heart diseases and climate change. Also, crowded cities worsen these concerns which means authorities must impose tough rules and switch to cleaner systems to lessen their damage. These problems can be addressed by having emission-tracking systems, making regulations stricter, educating the public and encouraging more sustainable ways to travel. Forecasting vehicle emissions using traditional and existing algorithms is not easy. First of all, standard approaches usually have simple models that do not fully consider all the relationships present in emission data. Because of this, predictions might not be correct and the results would not be reliable. It is challenging for linear regression and rule-based approaches to fully describe the way emission factors are related which reduces their accuracy. Because of the big amounts of data and the presence of nonlinear details in emission samples, algorithms such as decision trees and support vector machines may struggle. In addition, traditional models might not be able to keep up with shifting emission rates and environmental circumstances which often leads to lower performance in practice. All in all, since traditional methods have limits, using machine learning can help improve the accuracy of how emissions are expected to change. With the use of advanced tools such as deep learning and data visualization, the system lets people make decisions, act quickly and team up to cut down pollution and enhance air quality.

PROPOSED SYSTEM

To get more accurate and lower error forecasts than the listed models, this project uses an HSBUCF hybrid model that begins with stacking bi-directional LSTMs, then adds uni-directional LSTMs and finally ends with fully connected dense layers.

LSTMs are discussed using examples of uni-directional and bidirectional types. To find patterns in energy consumption,

bi-directional LSTMs process inputs from both the present and the recent past.

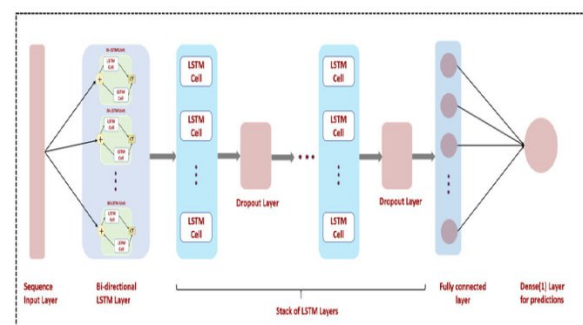
• UNI-DIRECTIONAL LSTMS(OR LSTMS)

Process, analyze and forecast data that is in a sequence. It uses data from the current instant and the results of the previous instant to make its prediction. In addition to using previous outputs for input, LSTMs also use their memory cells over a series of predictions to help with long-term tasks such as energy forecasting. Besides, thanks to gates and new recurrent parts, LSTMs are capable of handling information and defeating the difficulty of vanishing gradients.

Bi-Directional LSTMS

Bi-directional LSTM is improved upon uni-directional LSTM systems. The inputs are processed two times in LSTMs: the forward pass is done from early to late data and the backward pass is done from late to early data. By combining the hidden results from the forward and backward passes, the model can save information received from past and future data in separate hidden layers. After hiding, the output from these layers is sent to the only matching output layer. As a result, this technique allows the bidirectional LSTMs to remember the context and regularities from both old and new information much better, without any delays. It is known that bi-directional LSTMs provide better results than uni-directional LSTMs in areas such as speech recognition.

• Proposed Model Architecture



The architecture of the proposed HSBUCF model is clarified in Figure 5. The model has three types of layers: 1) a Bi-directional LSTM layer, 2) Stacked Uni-directional LSTM layers and 3) fully connected layers/dense layers. As we talked

about before, bi-directional LSTMs collaborate by using both forward and backward dependencies. The first layer of the bi-directional LSTM takes charge of extracting the temporal long-term dependences from the consumption values. Following this, LSTM layers which are good at understanding forward dependencies, are put in the top layers to take in outputs from the lower layer that has learned from the main features.

EXISTING SYSTEM

The approach to Vehicle Exhaust Emission Index (VEEI) currently depends on stationary tests during Pollution Under Control (PUC) checks. Doing these tests, Scientists study how much carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx) and particles (PM) are emitted from vehicles under standard test procedures.

• Emission Testing Centers

Owners of vehicles are required by authorities to visit an authorized emission testing center regularly for Pollution Under Control certification. In these testing centers, there are gas analyzers and smoke meters meant to record the amount of pollutants that vehicles give off. The testing sites are overseen and controlled by government organs responsible for environmental and air quality law.

• Static Tests

While vehicles are tested for emissions, their engines are run under set situations, including using a set revving speed. During the time the engine runs, emissions from the vehicle are measured with gas analyzers and smoke meters. All the tests are carried out the same way to make sure the results are always reliable.

• Pass/Fail Criteria

Emission levels found in the static tests are checked by comparing them to the predetermined levels specified by lawmakers. The standards commonly outline what levels of problem substances such as carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx) and particulate matter (PM) in vehicle emissions are acceptable. A PUC certificate is issued to cars that either match or do not exceed the required emission levels. If a vehicle puts out more

emissions than the standards allow, it will fail the test and need repairs to pass.

MODULES

1. Emission Tracker Web App

The Emission Tracker Web App serves as the user interface for the entire system. It allows users to access emission data, predictions, and alerts in a user-friendly manner. The web app provides visualizations of emission trends, historical data, and predictive analytics. Users can interact with the app to view emission levels by location, vehicle type, or time period.

EEINet Model: Build and Train

- **Import Dataset:** During this step, we bring in the dataset with vehicle emissions using DB, a major attribute being air quality parameters such as the particles PM2.5, PM10, ozone (O3), nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO) and other related pollutants.
- **Preprocessing:** Before analyzing data, missing values are dealt with, inaccurately entered data is corrected, unnecessary data is removed and missing data is filled in with suitable methods.
- **Feature Extraction:** The correlation matrix is examined to select highly related features which makes it possible to reduce the number of features and interpret model behavior better.

EEI Predictor

Car Exhaust Gas Value: Using real-time data, it monitors car exhaust gases, checking for levels of CO, NOx and HC among them.

EEI Prediction: To estimate the VEEI, the trained EEINet canalizes the exhaust gas measurements and other important details.

Location-Based Prediction: Provides location-based predictions, allowing users to understand emission levels and trends in specific geographical areas.

regulations instantly, so that action could be taken in time to protect the environment and the public.

JOURNAL REFERENCES

1. S. Sara et al., "The Application of Mobile Sensing to Detect CO and NO₂ Emission Spikes in Polluted Cities", IEEE Access, vol. 11, pp. 79624-79635, 2023.
2. J. Marques, S. F. A. Batista, M. Menendez, E. Macedo and M. C. Coelho, "From aggregated traffic models to emissions quantification: connecting the missing dots", Transportation Research Procedia, vol. 69, pp. 568-575, 2023.
3. Z. Wu, X. Huang, R. Chen, X. Mao and X. Qi, "The United States and China on the paths and policies to carbon neutrality", J. Environ. Manage., vol. 320, 2022.
4. R. Akhila, B. Amoghavarsha, B. Karthik, Y. Prajwal and Bajarangbali, "Internet of Things based Detection and Analysis of Harmful Vehicular Emissions", 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT), pp. 630-636, 2022.
5. Shakunthala, S. V. T. Sangeetha, M. Krishnammal and T. V. Padmavathy, "Intelligent Sensor and IoT Based Vehicle Pollution Monitoring System with Alert", 2022 International Conference on Power Energy Control and Transmission Systems (ICPECTS), pp. 1-4, 2022.
6. S. F. A. Batista, G. Tilg and M. Menéndez, "Exploring the potential of aggregated traffic models for estimating network-wide emissions", Transp. Res. D Transp. Environ, vol. 109, pp. 103354, Aug 2022.
7. E. Barmounakis, M. Montesinos-Ferrer, E. J. Gonzales and N. Geroli-minis, "Empirical investigation of the emission-macroscopic fundamen-tal diagram", Transp. Res. Part D Transp. Environ, vol. 101, pp. 103090, Dec 2021.
8. E. Taşören, H. Aydoğan and M. S. Gökmen, "Research of Effect on Gasoline-2-Propanol Blends on Exhaust Emission of Gasoline Engine with Direct Injection Using Taguchi Approach", European Mechanical Science, vol. 5, no. 4, pp. 177-182, 2021.
9. G. N. Ike, O. Usman and S. A. Sarkodie, "Fiscal policy and co₂ emissions from heterogeneous fuel sources in thailand: evidence from multiple structural breaks cointegration test", Science of the Total Environment, vol. 702, pp. 134711, 2020.
10. W. Zeng, L. Pang, W. Zheng and E. Hu, "Study on combustion and emission characteristics of a heavy-duty gas turbine combustor fueled with natural gas", Fuel, vol. 275, Sep. 2020.
11. S. Palzer, "Photoacoustic-based gas sensing: A review", Sensors, vol. 20, no. 9, pp. 2745, May 2020.
12. V. S. Esther Pushpam, N. S. Kavitha and A. G. karthik, "IoT Enabled Machine Learning for Vehicular Air Pollution Monitoring", 2019 International Conference on Computer Communication and Informatics (ICCCI), pp. 1-7, 2019.
13. M. Norhafana et al., "A review of the performance and emissions of nano additives in diesel fuelled compression ignition-engines", IOP Conf. Ser. Mater. Sci. Eng., vol. 469, no. 1, 2019.
14. L. Boppana, S. Rani and R. K. Kodali, "RFID based Vehicle Emission Monitoring and Notification System", TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON), pp. 1264-1269, 2019.
15. K. Gupta and N. Rakesh, "IoT Based Automobile Air Pollution Monitoring System" 2018 8th International Conference on Cloud Computing Data Science & Engineering (Confluence), pp. 14-15, 2018.
16. T. Schindele, "Vehicle noise emission legislation-opportunity for innovative exhaust system solutions", Proc. Inter-Noise Noise-Con Congr. Conf., vol. 255, no. 5, pp. 2095-2102, 2017.
17. K. Han, H. Liu, V. V. Gayah, T. L. Friesz and T. Yao, "A robust optimization approach for dynamic traffic signal control with emission considerations", Transp. Res. Part C Emerg. Technol, vol. 70, pp. 3-26, Sep 2016.
18. F. Karagulian et al., "Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level", Atmos. Environ., vol. 120, pp. 475-483, Nov. 2015.
19. H.-L. Chiang, P.-H. Huang, Y.-M. Lai and T.-Y. Lee, "Comparison of the regulated air pollutant emission characteristics of real-world driving cycle and ECE cycle for motorcycles", Atmos. Environ., vol. 87, pp. 1-9, Apr. 2014.

20. V. Franco, M. Kousoulidou, M. Muntean, L. Ntziachristos, S. Hausberger and P. Dilara, "Road vehicle emission factors development: A review", Atmospheric Environ., vol. 70, pp. 84-97, May 2013.

BOOK REFERENCES

1. "Python Crash Course" by Eric Matthes (Python Crash Course)
2. "Learning MySQL: Get a Handle on Your Data" by Russell J.T. Dyer (Learning MySQL)
3. "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow" by Aurélien Géron (Hands-On Machine Learning)
4. "Python for Data Analysis" by Wes McKinney (Python for Data Analysis)
5. "WampServer 2: Manually Installing the Apache, MySQL, and PHP" by Dr. James R. Small (WampServer 2)
6. "Bootstrap 4 Quick Start: Responsive Web Design and Development with Bootstrap 4" by Jacob Lett (Bootstrap 4 Quick Start)
7. "Fluent Python: Clear, Concise, and Effective Programming" by Luciano Ramalho (Fluent Python)
8. "High-Performance MySQL: Optimization, Backups, and Replication" by Baron Schwartz, Peter Zaitsev, Vadim Tkachenko (High-Performance MySQL)
9. "Python for Data Science For Dummies" by John Paul Mueller (Python for Data Science For Dummies)

WEB REFERENCES

1. Flask Documentation: Official documentation for Flask web framework - <https://flask.palletsprojects.com/en/2.0.x/>
2. MySQL Documentation: Official documentation for MySQL database management system - <https://dev.mysql.com/doc/>
3. TensorFlow Documentation: Official documentation for TensorFlow deep learning framework - <https://www.tensorflow.org/guide>
4. Pandas Documentation: Official documentation for Pandas data analysis library - <https://pandas.pydata.org/docs/>
5. Scikit-learn Documentation: Official documentation for Scikit-learn machine learning library - <https://scikit-learn.org/stable/documentation.html>

6. Matplotlib Documentation: Official documentation for Matplotlib data visualization library - <https://matplotlib.org/stable/contents.html>
7. NumPy Documentation: Official documentation for NumPy numerical computing library - <https://numpy.org/doc/stable/>
8. Seaborn Documentation: Official documentation for Seaborn statistical data visualization library - <https://seaborn.pydata.org/tutorial.html>
9. Bootstrap Documentation: Official documentation for Bootstrap CSS framework - <https://getbootstrap.com/docs/5.1/getting-started/introduction/>

