WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Proactive Monitoring and Prediction of Vehicle Exhaust Emissions for Enhanced Environmental Health

Vijay Kumar E, Purushoth B, Sreenath Vikram M

Department of Computer Science, Kingston Engineering College, Vellore
Email: vijaykumarelumalai123@gmail.com, sreenathv246m@gmail.com, purushothbabu8@gmail.com

T.PRIYA AP/CSE

Under the guidance, Kingston Engineering College, Vellore, Email:tpriya.engineering@kingston.ac.in

Abstract

The project introduces *Emission Tracker*, a real-time vehicle emission monitoring system using Long Short-Term Memory (LSTM) networks. It predicts Vehicle Exhaust Emission Index (VEEI) trends by analyzing carbon emission data. Featuring a web-based dashboard, the system provides location-based insights and predictive analytics, enabling proactive interventions to enhance air quality and promote environmental sustainability. It supports regulatory compliance through continuous tracking. The alert system notifies users of critical emission levels. This approach empowers decision-makers with actionable insights for pollution control.

Keywords:
Vehicle Exhaust Emission Index (VEEI), LSTM (Long Short-Term Memory),
Deep Learning, Real-time Monitoring, Predictive Analytics, Environmental Sustainability,
Web-based Dashboard, Emission Tracker, Air Quality, Pollution Control

1. Introduction

Vehicle exhaust emissions result from burning air-fuel mixtures in internal combustion engines, releasing pollutants like carbon dioxide, nitrogen oxides, and unburned hydrocarbons. These emissions vary based on fuel type and engine operation and are also produced during fueling and fuel evaporation. Major components include CO_2, nitrogen, water vapor, and oxygen, with smaller amounts of harmful substances like carbon monoxide and particulate matter. These pollutants significantly contribute to air pollution and climate change.

As vehicle usage continues to rise, managing these emissions becomes increasingly critical. Traditional testing methods are static and do not reflect real-time emission levels.

2. Related Work

Several studies and systems have been proposed to monitor and predict vehicle emissions using various technologies and methods:

1. **Carbon Emission Estimation Using Lifecycle Models**
   Zhao and Yang (2015) estimated CO_2 emissions of a chemical tanker using draft guidelines and energy efficiency indices. Their methodology highlighted the importance of lifecycle-based emission assessment but was limited to the shipping industry and lacked real-time capabilities.
2. **IoT and GNSS-Based Real-Time Monitoring**
   Thibault and Pognant-Gros (2018) introduced a system combining IoT devices, smartphone GNSS, and web-based simulations to monitor air pollution exposure during driving. While effective for real-time monitoring, it focused more on driver exposure than on predictive analytics or long-term trend forecasting.
3. **Improved Traffic Models for Emission Reduction**
   Wang and Ma (2018) proposed an improved Stop-and-Go model using connected vehicle data to reduce urban traffic emissions. This model significantly reduced NOx and CO emissions but required sophisticated vehicle communication systems and did not leverage machine learning for prediction.

4. **IoT-Based Emission Alert Systems**
   Devan (2019) developed a cost-effective IoT system to monitor hazardous gases from vehicles in real-time and send alerts via GSM. Though efficient in monitoring, it lacked predictive capabilities and used basic sensor thresholds without deep learning models.
5. **Artificial Neural Networks for Emission Prediction**
   Xu and Kang (2019) applied ANN models trained on remote sensing data to predict exhaust emissions. Their work demonstrated the potential of machine learning for accurate emission prediction, laying the groundwork for more advanced models like LSTM used in this project.

These works underscore the growing interest in real-time emission monitoring and prediction. However, many rely on traditional models or focus on immediate detection rather than long-term forecasting. The proposed **Emission Tracker system** addresses this gap by integrating deep learning (LSTM), real-time analytics, and location-based insights to proactively manage vehicle exhaust emissions.

3. Methodology

The proposed methodology involves collecting vehicle emission data from sensors and testing centers, followed by preprocessing to clean and standardize the dataset. Key features are selected using Recursive Feature Elimination and correlation analysis to enhance model performance. An LSTM-based deep learning model is then trained to predict the Vehicle Exhaust Emission Index (VEEI) over time. The model is integrated into a web application for real-time monitoring, visualization, and alert generation.

4. System Architecture and Implementation

The system is built on a Python/Flask backend with MySQL for database management, hosted locally via WampServer. Machine learning models (e.g., LSTM-based EEINet) leverage TensorFlow/SciKit-Learn for emission prediction, while Bootstrap ensures a responsive frontend. Key modules include real-time EEI prediction, an alert system (SMS/email), and role-based access for stakeholders (Admin, RTO, CPCB, Vehicle Owners). Data pipelines integrate preprocessing (RFE, correlation matrices) and visualization (Matplotlib/Seaborn) for actionable insights. The system enables regulatory compliance, emission tracking, and proactive air quality management.

5. Results and Discussion

The Emission Tracker system successfully integrates machine learning (LSTM-based EEINet) with real-time monitoring to classify vehicle emissions into four categories: Good, Satisfactory, Poor, and Phase Out.Key Results:

1.

2.**Model Performance:**

•The EEINet model achieved ~92% accuracy in predicting the Vehicle Exhaust Emission Index (VEEI) after hyperparameter tuning and feature selection (RFE + Correlation Matrix).

•LSTM networks effectively captured temporal patterns in emission data, improving prediction reliability compared to traditional regression models.

3.Real-Time Prediction & Alerts:

•The system processes real-time sensor data (CO, NOx, HC) and triggers SMS/email alerts when emissions exceed regulatory thresholds, enabling timely interventions.

4.Stakeholder Impact:

•CPCB/RTO Admins efficiently monitor compliance, ban non-compliant vehicles, and generate compliance reports.

•Vehicle Owners receive PUC certificates and personalized alerts, improving adherence to emission norms.

Discussion:

•The Flask-based web app provided a scalable interface, though cloud deployment (e.g., AWS/Azure) could enhance accessibility beyond local hosting (WampServer).

•Data quality challenges (missing values, outliers) were mitigated via preprocessing, but integrating IoT sensors could improve real-time data accuracy.

6. Conclusion and Future Work

Conclusion:

The Emission Tracker system successfully bridges AI-driven analytics (LSTM-based EEINet) with stakeholder collaboration to combat vehicular pollution. By delivering real-time predictions (~92% accuracy), automated alerts, and role-specific dashboards, it empowers regulators (CPCB/RTO), vehicle owners, and admins to enforce compliance and reduce emissions proactively. The project underscores the potential of machine learning in environmental sustainability, fostering data-driven decision-making for cleaner air.

Future Work:

1.IoT Integration – Deploy low-cost sensors for hyperlocal, real-time emission monitoring.

2.Air Quality Forecasting – Combine emission data with weather/traffic models for predictive pollution alerts.

3.Smart City Synergy – Integrate with traffic management systems to optimize emission hotspots dynamically.

4.Edge AI – Implement lightweight models for onboard vehicle diagnostics to reduce cloud dependency.
5.Policy Tools – Expand analytics to simulate emission impacts of regulatory changes (e.g., fuel standards).
By prioritizing scalability and interoperability, the system can evolve into a global benchmark for intelligent emission governance.

7. Limitations and Recommendations

Limitations: The system's accuracy depends on data quality and may face latency in real-time predictions due to local hosting. Limited sensor coverage and static emission thresholds also restrict adaptability.
Recommendations: Expand data sources with IoT sensors, migrate to cloud/edge computing for scalability, and adopt dynamic emission benchmarks. Optimizing lightweight AI models and stakeholder training can further enhance efficiency.
Future Focus: Prioritizing these improvements will strengthen the system's reliability and policy responsiveness for broader environmental impact.