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A Systematic Review on the Development of Emission Inventory Models Using Artificial Intelligence with Image-Based Vehicular Air Pollution Detection in Urban Traffic Environment

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Abstract

The increasing burden of vehicular air pollution in urban environments has necessitated the evolution of emission inventory models, particularly through the integration of Artificial Intelligence (AI) techniques. This systematic review investigates past and current research focused on the development and application of AI-driven emission inventory models, with a special emphasis on image-based air pollution detection and vehicle classification in congested traffic areas. The review compiles and analyzes over 25 peer-reviewed articles, technical reports, and case studies published between 2009 and 2024, highlighting the use of machine learning, computer vision, and deep learning techniques to estimate pollutant emissions such as PM2.5, NOx, CO, and VOCs in metropolitan cities. Particular attention is given to methodologies that use traffic camera images, drone footage, and surveillance systems for real-time detection and classification of vehicle types and traffic density, serving as proxies for emission estimates. The study identifies major gaps in spatial-temporal resolution, data validation techniques, and integration with official emission inventories. Finally, it offers future research directions including hybrid models combining AI and traditional inventory methods, heat mapping in urban environments, city-specific calibration, and policy-level applications. This review supports the foundation for advanced, real-time, and scalable emission modeling tools tailored for smart city air quality management.

Keywords: Emission inventory models; Artificial Intelligence; Emission inventory; Machine learning; Image-based detection; Vehicle classification; Heat Mapping

1. Introduction

The rapid development in urban India has resulted in a tremendous increase in the number of motor vehicles. In some cities, this has doubled in the last decade. Rapid urbanization and growth of motor vehicles impose a serious effect on human life and the environment in recent years. Motor vehicles are a significant source of urban air pollution and are increasingly important contributors of anthropogenic carbon dioxide and other greenhouse gases. Transport sector contributes a major sector, contributing 90% of total emissions. Air pollution is a serious environmental health threat to humans. Adverse effects range from nausea, difficulty in breathing and skin irritations, birth defects, immunosuppression and cancer. All these situations indicate that air pollution becoming a major problem in Indian context and there is an essential need to build up healthy environment and increase the level of research around the world. Indian cities are facing the problem of severe air pollution and vehicles are a major source. The economically vibrant cities like Delhi, Bengaluru, Chennai, Hyderabad, Mumbai provide numerous job opportunities and hence have a large vehicle population. These cities thus contribute the largest share in emissions of pollutants. Other growing cities like, Jaipur, Pune, Coimbatore, Nagpur are also emitting a lot of pollutants [1]. Urbanization and rapid motorization have significantly increased vehicular emissions, contributing to deteriorating air quality in major cities worldwide. Vehicular pollution, comprising pollutants such as particulate matter (PM), nitrogen oxides (NO_x), carbon monoxide

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(CO), hydrocarbons (HC), and volatile organic compounds (VOCs), poses severe health risks and environmental challenges. In India, metropolitan areas like Mumbai, Pune, and Nagpur have witnessed a sharp increase in air pollution due to high vehicle density and inadequate traffic management strategies. To tackle this challenge, Emission Inventory Models (EIMs) are used to estimate pollutant loads from various sources. These models are crucial tools for understanding emission sources, evaluating policy measures, and supporting urban air quality management[2]. Traditional emission inventories often rely on manual data entry, on-ground surveys, or averaged fuel consumption figures. However, they are often limited in spatial and temporal resolution, and may not reflect real-time conditions in complex urban settings.

With the advancement in data science, Artificial Intelligence (AI) offers powerful techniques to enhance emission inventory development. AI models such as machine learning (ML) and deep learning (DL) can process large-scale heterogeneous data from sources like traffic sensors, weather stations, satellite imagery, and vehicular activity logs. For example, algorithms such as Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs) have been applied to predict air quality, classify vehicle types, and estimate emission levels [3,4]. A particularly promising approach is the use of image-based AI techniques, such as computer vision, for detecting vehicular emissions. Real-time traffic images from CCTV or drone footage can be processed using CNNs and object detection models (e.g., YOLO, Faster R-CNN) to count vehicles, classify types (e.g., trucks, cars, two-wheelers), and correlate them with emission profiles[5,6]. These image-based systems provide dynamic, high-resolution data that can be integrated into AI-powered emission inventory models, enhancing accuracy and timeliness.

This systematic review focuses on recent advancements in the development of emission inventory models using artificial intelligence, particularly those integrating image-based detection techniques in urban traffic environments. It explores the intersection of AI, computer vision, and environmental monitoring, aiming to identify current capabilities, challenges, and future directions.

Objectives of the Study

- To review AI techniques applied in emission inventory modeling.
- To identify research gaps and potential improvements in AI-driven emission estimation for urban traffic.

2. Literature review

Literature Review Section with Thematic Breakdown

2.1. Overview of Traditional Emission Inventory Models

Early emission inventory systems, such as COPERT, EMEP/EEA, and INTAKE, focused on static inputs like fuel sales, vehicle registration, and average mileage. These methods lacked real-time data responsiveness and granularity, particularly in congested urban areas[2].

2.2. Integration of Artificial Intelligence in Emission Modeling

AI has increasingly been used to address limitations in traditional inventories:

- Regression Models & Neural Networks: AI models predict emission concentrations based on traffic, weather, and sensor inputs and provides *health justification* for AI-based accurate emission prediction [3,7].
- Decision Trees & Random Forests: Used for source apportionment and pollution forecasting and provides *global mortality evidence* supporting improved AI-based emission estimation [4,8].
- Deep Learning (DL): For identifying emission patterns from high-dimensional datasets and provides *traffic-flow and heat-pattern insights* useful for deep learning models[9,10].

These methods provide adaptive and data-driven solutions capable of handling complex, nonlinear interactions in urban systems.

2.3. Computer Vision and Image-Based Vehicle Analysis

Recent breakthroughs in deep learning, particularly CNN-based models like YOLO, Mask R-CNN, and Faster R-CNN, have enabled real-time:

- Vehicle detection and classification (e.g., car, truck, two-wheeler).
- Emission estimation through integration with license plate databases or known emission factors [5].
- Traffic flow analytics for congestion-related pollution inference [6].

This opens new opportunities to build visual emission inventory models based on urban surveillance infrastructure.

3. Methodology

To understand the evolution and application of emission inventory models and AI-based approaches in vehicular air pollution research, a structured literature review was conducted. The selected studies span from 2009 to 2024 and include traditional bottom-up inventory methods, AI-enabled traffic monitoring, real-time forecasting, image-based detection, and hybrid deep learning models. Each study was evaluated based on its focus area, methodology used, and key contributions to the domain. Table 1 presents a chronological summary of these representative works, highlighting advancements in both emission quantification techniques and intelligent air quality assessment frameworks.

Table 1 Summary of Key Papers in the Review

Author(s)	Year	Focus Area	Methodology	Key Contribution
Ntziachristos et al.	2009	Traditional Emission Inventory	COPERT Method	Developed baseline European mobile source emission model
Sharma et al.	2011	Vehicle Growth in India	Statistical Analysis	Explored impact of demographic/economic trends on motor vehicle growth
Gasana et al.	2012	Health Impacts of Vehicular Air Pollution	Meta-analysis of epidemiological studies	Demonstrated strong association between vehicular pollutants
Goyal et al.	2013	Delhi Emission Inventory	Bottom-Up Inventory	Created vehicular pollutant inventory for Delhi city
Jing et al.	2016	High-Resolution Emission Inventory	NRT Traffic + Spatial Modeling	Created dynamic vehicular emission inventory for Beijing using real-time traffic
Nagpure et al.	2016	Exhaust & Non-Exhaust Emissions	Emission Inventory (Delhi)	Estimated PM, air toxics from vehicles using local factors
Redmon et al.	2016	Object Detection in Images	YOLO (You Only Look Once)	Pioneered real-time deep learning object detection algorithm (YOLO)
Zhu et al.	2017	Traffic Flow & Urban Heat Mapping	Cell Transmission Model (CTM), traffic-flow heat simulation	Showed how vehicle density influences heat intensity and pollution hotspots
Bang & Khue	2018	General Air Emission Inventory	Review & Framework Design	Outlined emission quantification methods for gases and particles
Polk	2019	Global Air Pollution Exposure	Epidemiological Review	Presented global air quality and disease burden data
Zhang et al.	2019	Air Quality Forecasting	Machine Learning (Random Forest, ANN)	Predicted pollutant levels from meteorological data
Anenberg et al.	2019	Global Transportation Emission Burden	Atmospheric modelling (GEOS-Chem), global mortality	Provided global justification for improved emission models
Kumar et al.	2020	Urban Emission Modeling	Ensemble ML	Identified urban pollution hotspots via AI

Meng et al.	2020	Real-time Emission Estimation	Web-Based Traffic Data	High-resolution spatial & temporal distribution of vehicle emissions
Mandal et al.	2020	AI-based Traffic Monitoring	AI-Driven Systems	Developed AI-enabled smart traffic and pollution monitoring infrastructure
Bai et al.	2021	AI Forecast Models	LSTM Deep Learning	Forecasted urban emissions from sequential traffic data
Chen et al.	2021	Vehicle Detection	YOLO, Image AI	Real-time vehicle classification using CCTV images
Lokhande et al.	2021	Vehicular Pollution Impact	Emission inventory approach	Developed city-scale PM emissions inventory for dispersion modeling
Umair et al.	2021	Traffic Queue Detection	Video Analytics, Deep Learning	Estimated vehicle queue length for emissions using video-based computer vision
Li et al.	2022	Smart Inventory Modeling	Computer Vision + Emission Factors	Mapped emissions using image-based vehicle classification
Tiwari et al.	2022	PM2.5 Forecasting (India)	CNN-GRU Hybrid DL	Improved accuracy of particulate pollution forecasting in Indian metros
Gao et al.	2023	Real-time Urban Emissions	AI with Remote Sensing	Developed integrated AI pipeline for emission detection using satellite and drones
Singh & Mehta	2023	AI in Traffic Emission Inventory	ML + Edge Devices	Enabled decentralized pollution data collection via smart traffic infrastructure
Roy et al.	2024	Emission Inventory Automation	AI + IoT Systems	Developed scalable automated emission monitoring system for Indian cities
Patel et al.	2024	Air Quality and Health	Meta-analysis + AI Search Algorithms	Synthesized epidemiological links between pollutants and public health outcomes

4. Results and discussion

The reviewed literature from 2009 to 2024 reveals a clear technological progression from traditional emission inventory models to sophisticated AI-enabled real-time monitoring systems. Early studies such as Ntziachristos et al. (2009) and Goyal et al. (2013) established foundational bottom-up inventories based on vehicle type and fuel consumption. By contrast, more recent work—such as Li et al. (2022), Gao et al. (2023), and Roy et al. (2024)—leverages computer vision, IoT, deep learning, and remote sensing to estimate and map vehicular emissions in real-time.

- **AI Models Adopted**: A wide range of AI techniques were applied, including heat patterns useful for emission hotspot identification (Zhu et al., 2017), Random Forest (Zhang et al., 2019), LSTM (Bai et al., 2021), CNN-GRU hybrids (Tiwari et al., 2022), and YOLO-based image classification (Chen et al., 2021).
- **Application Areas**: Applications include air quality forecasting, queue length detection, real-time vehicle classification, automated emission inventorying, and exposure-health impact estimation.
- **Spatial Coverage**: While foundational emission inventory research has been predominantly conducted in Europe and select Indian metropolitan cities like Delhi and Mumbai, recent studies have broadened their geographic scope. Notably, there is increased research activity in rapidly urbanizing Asian regions such as China, particularly in megacities like Beijing and Shanghai. However, despite this expansion, significant spatial disparities remain—especially in Indian smart cities such as Pune and Nagpur, where dynamic emission modeling using AI techniques is still underrepresented.

5. Research gaps identified

Identified Research Gaps and Need for AI-Driven Solutions, although substantial advancements have been made in vehicular emission monitoring and modeling, a critical analysis of recent literature reveals several unresolved challenges. Many existing studies adopt isolated approaches, targeting specific components such as vehicle detection or pollution forecasting, without integrating them into a complete pipeline that spans from vehicle recognition to emission estimation and health impact assessment. Moreover, validation using real-world field data or localized health statistics is often lacking, reducing the robustness of AI models. Emission studies tend to be concentrated in major metropolitan areas like Delhi, while rapidly urbanizing smart cities such as Pune and Nagpur remain underexplored. Additionally, short training periods limit model adaptability to long-term trends, and most efforts ignore non-exhaust sources like tire and brake wear or idle-time emissions during traffic congestion. To address these limitations, the following Gap–Solution Matrix outlines the key research deficiencies and suggests actionable AI-driven approaches to bridge them in the table 2.

Table 2 Gap–Solution Matrix for AI-Based Vehicular Emission Studies

Research Gap	Proposed AI/Technical Solution
Lack of Integrated Frameworks	Develop end-to-end AI pipelines (vehicle → emission → health impact)
Limited Ground Truth Validation	Incorporate field measurement data and hospital records to validate AI predictions
Underrepresented Smart Cities	Expand AI-based emission research to Tier-2 and emerging smart cities like Pune, Nagpur
Short Training Timeframes	Use long-term, multi-year, and seasonal datasets to improve forecasting models
Non-Exhaust Emissions Ignored	Include tire wear, brake dust, and road resuspension in AI-based inventory models
Idle-Time Emissions Unaccounted	Use traffic jam detection from CCTV/drones to estimate emissions during vehicle idling
Image-Based Mapping Underused	Integrate image-based vehicle detection with GIS to create spatial emission heatmaps
Multi-Modal Traffic Oversight	Train models to handle diverse vehicle types common in Indian traffic (2W, autos, HDVs, etc.)
Limited linkage between emission models and real health outcomes	AI models can be integrated with health datasets to create advanced exposure–response systems.
Lack of traffic-flow–based spatial emission hotspot detection	Deep learning models using CNNs and heat-map techniques can convert traffic-flow patterns into high-resolution pollution hotspot maps.

Despite growing interest in AI-driven environmental modeling, several critical gaps persist in the current body of literature. The majority of studies emphasize pollution level forecasting rather than comprehensive emission inventory estimation, which is vital for urban planning and regulatory action. There is a noticeable lack of integration across multiple data sources—including real-time images, sensor networks, and IoT-based traffic monitoring—which limits the contextual accuracy of predictions.

6. Conclusion

This systematic review highlights the growing intersection between AI technologies and vehicular emission inventory models. From the baseline methodologies in 2009 to state-of-the-art applications in 2024, there is clear evidence of AI's ability to enhance accuracy, spatial granularity, and real-time response in emission forecasting. However, integration challenges, data quality limitations, and validation gaps still constrain the deployment of AI-based systems in policy frameworks.

6.1. AI Application Areas in Vehicular Emission Studies

[Traffic Camera / Drone Feed]

↓

[Image Preprocessing / Segmentation]

↓

[Vehicle Detection & Classification (CNN/YOLO)]

↓

[Traffic Density Estimation]

↓

[Emission Factor Estimation (per vehicle type)]

↓

[Pollutant Estimation (CO, NOx, PM2.5)]

↓

[Emission Inventory Model Output]

6.2. Policy recommendations

Based on the review, the following policy recommendations are proposed:

- **Mandate AI-Integrated Emission Monitoring**: Government agencies should incentivize cities to adopt AI-driven emission inventory tools, especially in air quality non-attainment areas.
- **Open Data Frameworks**: Central and state pollution boards should enable open access to vehicular, meteorological, and air quality data to support AI training and transparency.
- **City-Specific Emission Baselines**: Emission factors should be updated using localized driving conditions, fuel quality, and vehicle age, especially for Indian cities.
- **Cross-Sector Collaboration**: Integrate AI-based traffic and pollution monitoring tools into urban mobility planning, health policy, and smart city architecture.
- **Include Non-Exhaust Emissions**: Broaden emission regulations to include tire wear, brake dust, and road dust—particularly in policies governing electric and hybrid vehicles.

6.3. Future work and research directions

Building upon the insights from this systematic review, future research will focus on the development of a real-time, AI-based emission inventory model tailored to the urban contexts of Pune, Mumbai, and Nagpur. The goal is to create a dynamic system that captures vehicular activity, estimates corresponding emissions, and informs evidence-based urban and environmental policy. Key directions include:

- **AI-Powered Image-Based Emission Mapping**: Integrating real-time CCTV and drone-based vehicle classification (using models like YOLO or Faster R-CNN) with standard emission factor databases to generate spatially-resolved, image-driven emission maps that visualize urban pollution hotspots.

- **Forecasting Traffic-Linked Pollutants**: Using advanced time-series models such as SARIMA, LSTM, and Prophet to project pollutant concentrations (especially $PM_{2.5}$ and NO_x) in response to changing vehicular trends, congestion patterns, and meteorological variables. These forecasts will be linked to public health data, particularly respiratory indices and hospital admission rates.

- **Traffic Jam and Idle-Time Emission Estimation**: Capturing vehicle idling periods and queue lengths from traffic congestion using computer vision techniques to estimate excess emissions generated during prolonged traffic jams—an often overlooked but significant source of urban air pollution.
- **Vehicle Activity-Based Inventory Enhancement**: Leveraging license plate recognition and VKT (Vehicle Kilometers Traveled) estimation from traffic camera footage to compute dynamic emission factors and assess emissions under real-world driving conditions, including start-stop cycles and peak-hour traffic behavior.
- **Smart City and Tier-2 Urban Expansion**: Extending the application of these models beyond metropolitan centers to fast-growing Tier-2 smart cities, assessing how traffic mix, density, and infrastructure influence emissions and model scalability.
- **Field Validation with Multisource Data**: Cross-validating AI-generated emissions data using ground truth from field sensors, portable air quality monitors, traffic signals or in heavy traffic areas and hospital-level epidemiological data (e.g., asthma, COPD cases), ensuring model robustness and practical applicability.
- **Development of a Decision Support Dashboard**: Creating an interactive, real-time urban emissions dashboard for municipal authorities and pollution control boards. This tool will allow policymakers to visualize emissions trends, predict pollution events, and simulate the impact of interventions like traffic rerouting, vehicle bans, or green zone expansion.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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