AI-Based Emission Inventory Modeling: A Comparative Study for Environmental Monitoring

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ABSTRACT

Air pollution in metropolitan cities such as in India has significantly increased due to fast urbanization and consistently rising number of vehicles along with its motor activity. Pollutants such as Nitrogen Oxides (NOx), Sulphur Dioxide (SO_2), Particulate Matter ($PM_{2.5}$, PM_{10}), Hydrocarbons (HC), Carbon Monoxide (CO) and others are important components emitted by the vehicle which have negative impact on the environment and human health. Precise emission inventory estimation is crucial for developing management plans and policies for air quality.

In the present study, an Artificial Intelligence (AI) based grid-wise vehicular emission inventory model for two prominent cities of India Nagpur and Mumbai are developed. Combines traditional bottom-up and top-down emission inventory methods with cutting-edge AI technologies to enhance emission estimation and prediction for vehicles. The use of traffic activity data, vehicle registration records, meteorological parameters, road network information and traffic imagery. Vehicle count, vehicle category, traffic density, and traffic speed information are extracted from traffic images and video using deep learning models such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and vehicles identification algorithm YOLO.

Studying this is done using a spatial grid-based approach to analysing the dispersion of emissions within urban areas and temporal variations over hourly, daily and seasonal scales. Their comparative study with the emissions produced at Mumbai shows that there are significant variations in emissions because of the population density, the traffic composition and the urban infrastructure. Incorporated with AI, this emission inventory model with enhanced accuracy and efficiency offers significant improvement from the typical approach to valuable insights for sustainable transportation planning and air pollution mitigation measures.

Keywords: Vehicular Emission Inventory, Artificial Intelligence, CNN, RNN, YOLO, Grid-Based Modeling, Air Pollution, GIS, Traffic Emissions

INTRODUCTION

Air pollution is currently one of the most severe environmental challenges faced globally and especially in rapidly urbanizing and motorising developing countries. In India over the last 20 years, there has been a significant growth in the number of vehicles held as well as their energy consumption and emissions from transportation. Road transport emissions play a crucial role in urban air pollution and have an impact on air quality, climate change and a wide range of public health challenges.

Emission inventories are a fundamental tool to provide information about the amount of pollutant emitted by various sources and their distribution in space and time. The basic statistical models and traffic activity data are the main input into traditional emission inventory models. However, these approaches are rather limited in their

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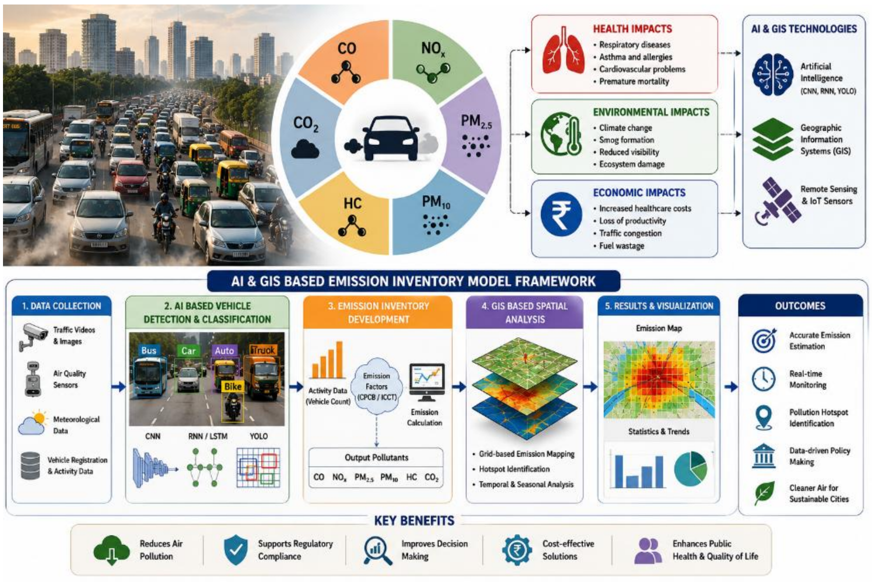
temporal resolution, or are not as confident, notwithstanding suboptimal traffic data quality, variability of vehicle operating conditions.



New opportunities for improving emission inventory development include recent developments in Artificial Intelligence (AI), machine learning (ML), computer vision, and geographic information systems (GIS). AI-driven methods are capable of automatically extracting traffic data from photos and videos, enhances the accuracy of estimating emissions, and predict future emissions scenarios.

In the present study, an AIIG-VEI Model is developed to estimate the emissions of vehicles operating in Nagpur and Mumbai cities in a grid-based manner. The study not only combines the traditional emission inventory methodology with advanced AI algorithms but also seeks to establish a comprehensive framework for the spatial and temporal evaluation of vehicular emissions.

LITERATURE REVIEW

Chelani and Devotta (2007) analyzed the impact of implementation of Compressed Natural Gas (CNG) on air quality problem of Delhi. They studied the pollution levels of air before and after CNG & observed significant reduction in pollution levels like particle matter and taking down other negative emissions as a result of using CNG. The study emphasized the importance of using cleaner fuel technologies in order to reduce the levels of urban air pollution and improve environmental quality.

Gurjar et al. (2010) presented research on air pollution in major cities throughout the world and how this will be affecting human health. The research exposed the importance of the contribution of the transportation sources to air pollution in the urban context and the impacts of this in terms of health issues. The authors suggest that developing an emission inventory is an important step in developing pollution abatement programs and that the planning of pollution abatement can contribute to optimizing health outcomes for the population.

Nagpure et al (2011) studied the correlation between the air quality deterioration, rapid urbanisation & growth of vehicles. They have concluded there's a strong correlation between pollutant emissions and increased vehicle usage and the growth of urban development. The importance of having reliable inventory of vehicle emissions, which is necessary to implement sustainable urban mobility and enhance environmental management, was part of the finding.

The effects of traffic and meteorological conditions on vehicular emissions were analyzed by Pandey et al. (2012). The study showed the impact of various factors like traffic congestion, temperature, wind speed and humidity in relation to emission levels and pollutant dispersion. The authors emphasized that the meteorological conditions need to be taken into consideration when preparing emission inventory models, to consider the uncertainty of the emission inventory modelling process.

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Singh and Pandey (2013) have analysed the air pollution in the cities as a spatial analysis using GIS. They have already demonstrated effectiveness of GIS solutions in the identification of pollution hot spots and knowledge of the spatial distribution of emissions. The study offered important insights into the use of GIS for integrating with emissions inventory development.

The On-road vehicular emission inventory was developed for Lucknow city, India by Shukla & Alam (2014), using GIS. By using traffic activity data, the vehicle categories and the emission factors, the pollutant emission at certain locations was estimated. The results demonstrated the usefulness of the GIS tools to generate detailed spatial emission map of urban transportation systems.

LeCun, Bengio and Hinton (2015) gave an advance survey of deep learning and its application to pattern recognition, image processing and artificial intelligence in general. The results of the deep neural networks they built served as a model for other complex applications in the transportation and environment sectors. This research had a significant impact on later research on traffic monitoring and emission estimation using artificial intelligence.

YOLO (You Only Look Once) is an object detection framework that was developed by Redmon et al. (2016), which revolutionized image recognition field and vehicle detection in the real-time processing arena. Overall, the model attained a very high level of accuracy of detection and reacts very quickly, making it very compatible with the monitoring system developed for the traffic. Ever since that time, YOLO has become one of the best machine learning models for vehicle recognition and speed analysis.

For time-series prediction and sequential data analysis, Hochreiter and Schmidhuber (2017) talked about a special type of Recurrent Neural Networks (RNN), the Long short term memory networks (LSTM). They also played an important role in developing a scientific basis for forecasting traffic flow and future emissions from their vehicles, making vital contributions to AI-based environmental modelling.

Kumar et al. (2018) has given an extensive overview of the growing applications of cheap, sensor technologies where air pollution measurements were being made in the urban setting. The study highlighted the value of continuous measurement of the environment and the value of real-time data collection. The authors pointed out that the air quality assessment and emissions control can be supported by incorporating sensor network technology and intelligence analytics.

Beig et al. (2019) calculated the air pollution exposure in cities of India and contribution from different emission sources. They noted that the main causes of urban air pollution are the emissions from vehicles. The issue of developing a sound emission inventory for policy formulation in the environment was also emphasized in the study.

Beig et al. (2020) created a detailed emission inventory of anthropogenic $PM_{2.5}$ and PM_{10} emissions for India. Sahu et al. (2020) have developed a comprehensive emission inventory anthropogenic $PM_{2.5}$ and PM_{10} emissions for India. They found major emission sources to be transportation, industrial activities and energy generation. The study provided an excellent inventory database which could be used for air quality modelling development and publication and the necessity of emission inventories for pollution mitigation activities became evident.

Guttikunda, Nishadh and Jawahar (2021) assessed Air Pollution Knowledge and characteristics of emission in the cities in India. They only became realised that inventories of regional emissions were needed and that efforts for the management of urban air quality needed to be more effective. The study highlighted the benefits of using advanced analysis tools in environmental decision-making.

Mangaraj et al. (2022) developed and analysed a comprehensive EI for the city of Bengaluru. The research utilized the activity data, emission factors and spatial analysis methods for the quantification of urban air pollutant emissions. The city-carbon accounting studies emphasized the need for city level emission inventories to identify 'hot spots' of emissions and to base actions for the ensuing mitigation.

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Sahu et al. (2023) have studied an increase in air pollutant emission in Delhi over the decade period. With the fast urbanization, population and transport growth, they discovered that the emission load has a good magnitude. The research highlighted the need for regular monitoring, and upkeep of the emissions to ensure sustainable urban development.

In 2024, Shukla, Singh and Kumar built the advanced GIS based vehicular emission inventory model which includes exhaust and fugitive emissions. Their research illustrated a more precise spatial description of the pollution sources and highlighted the importance of using a geospatial approach, complementing that by emission inventory methodologies, in urban air quality assessment.

Ghosal et al., (2025), developed a novel gridded emission inventory method that uses a super-resolution satellite-derived emission map based on object detection. They applied Artificial Intelligence and remote sensing to estimate and enhance the traffic activity and air quality forecasting. Their findings represent important strides towards building emissions inventories with AI and offer insight into the future possibilities of melding machine learning, computer vision, and geospatial technologies in environmental science.

Objectives of the Study

1. To develop a grid-based vehicular emission inventory model by integrating Artificial Intelligence techniques with conventional emission estimation methods.

2. To assess and compare vehicular emission levels in Nagpur and Mumbai cities considering different vehicle categories, fuel types, and traffic characteristics.

3. To examine the spatial and temporal distribution of vehicular emissions and predict future emission scenarios using Artificial Intelligence and Machine Learning models.

RESEARCH METHODOLOGY

Study Area

This study emphasizes the study of two cities attached to the state of Maharashtra, one is Nagpur and the other is Mumbai.

Data Collection

In most instances, the primary data sources of the present study are secondary data obtained from different governmental agencies, transportation departments, environmental groups and public databases. The traffic data, vehicle registration statistics, road network information, fuel consumption statistics and emission factors were obtained from official reports and published literature. To investigate the effect of meteorological parameters on vehicular emissions, the data pertaining to temperature, humidity, wind speed, precipitation, and weather conditions for each season was taken from various meteorological databases including the India Meteorological Department (IMD).

For data analysis, we relied on conventional data and traffic images and video recordings from traffic surveillance cameras, satellite imagery, as well as open-source geographic data platforms to support our Artificial Intelligence (AI) data analysis. Using deep learning methods, categories of vehicles, traffic level, and vehicle movement patterns within the images and videos were identified. For the preparation of emission inventory maps in a grid-based approach, Geographic Information System (GIS) data such as road networks and spatial boundaries has been gathered.

The study included various vehicle types including two-, three-, passenger cars, buses, light commercial, heavy-duty vehicles and fuel types using petrol, diesel, CNG and electric. Temporal variations were also emphasised by adding seasonal data. The data collected were pre-processed and validated and incorporated into the emission inventory framework for estimating and comparing emissions from the vehicles of Nagpur and Mumbai cities.

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Emission Inventory Development

Bottom-Up Approach

$$Q_{ij}^{p} = \sum(EF_{c,v}^{p} \times VT_{ij} \times VKT \times L_i)$$

where:

- Q_{ij}^{p}= Emission of pollutant p
- $EF_{c,v}^{p}$= Emission factor
- VT_{ij}= Traffic volume
- VKT= Vehicle kilometers travelled
- L_i= Road segment length

Top-Down Approach

Emissions are estimated using:

- Registered vehicle population
- Fuel consumption statistics
- Population data
- Average VKT

AI-Based Traffic Analysis

- CNN for vehicle classification
- YOLO for vehicle detection
- RNN/LSTM for emission forecasting
- Deep learning for traffic density estimation

Grid-Based Spatial Analysis

- Division of study area into uniform grids
- GIS mapping of emission hotspots
- Spatial interpolation and visualization

Temporal Analysis

- Hourly emissions
- Daily emissions
- Seasonal emissions
- Future forecasting scenarios

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Analysis of the study:

Table 1: Vehicular Population in Nagpur and Mumbai

Vehicle Category	Nagpur (Nos.)	Mumbai (Nos.)
Two-Wheelers	1,250,000	3,850,000
Three-Wheelers	65,000	175,000
Cars	450,000	1,850,000
Buses	8,500	18,000
Heavy Vehicles	35,000	95,000
Total	**1,808,500**	**5,988,000**

Analysis

In Mumbai people are much more dependent on transportation facilities than in Nagpur. Two-wheelers make up the biggest contribution in the cities' vehicle fleet. More passenger cars and commercial vehicles in Mumbai are a significant source of overall vehicle emissions.

Table 2: Estimated Annual Vehicular Emissions (Tonnes/Year)

Pollutant	Nagpur	Mumbai
CO	12,850	42,500
NOx	5,250	18,750
$PM_{2.5}$	1,120	4,250
PM_{10}	1,950	7,100
HC	3,850	11,950
CO_2	2,850,000	9,450,000

Analysis

Despite the higher emission levels, the pollutants' levels in Mumbai are significantly higher than those in Nagpur because of the higher traffic density along with vehicle population. Transportation activities are the largest contributors of CO_2 emissions, reflecting the importance of transportation in the production of total greenhouse gases.

Table 3: Seasonal Variation in Vehicular Emissions (CO_2 Tonnes/Day)

Season	Nagpur	Mumbai
Summer	7,200	24,500
Monsoon	6,850	23,100
Winter	8,100	26,800

Analysis

The emissions from vehicles show seasonal differences. Both cities experience peak emissions during the winter because emissions are higher when fuels are used, and there is less air dispersion of the pollutants. The emission levels from monsoon are comparatively low due to lower traffic density and pollutants removed due to rainfall.

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Table 4: Emissions by Vehicle Category

Vehicle Category	Nagpur	Mumbai
Two-Wheelers	8,250	25,450
Three-Wheelers	1,250	3,250
Cars	5,850	18,950
Buses	1,750	5,250
Heavy Vehicles	6,850	22,500

Analysis

Although as many or fewer, heavy-duty vehicles and passenger vehicles play a large role in the emission of pollutants. The findings suggest that emission control measures should focus on commercial transport and high consuming vehicles more

Table 5: Grid-Based Emission Distribution

Grid ID	Nagpur (kg/day)	Mumbai (kg/day)	Hotspot Status
G1	520	1,850	Moderate
G2	1,250	4,520	High
G3	850	3,250	High
G4	420	1,450	Moderate
G5	1,480	5,250	Very High

Analysis

The analysis through the grid methodology defines the main corridors for transportation and the areas where commercial activities take place as sources of emissions. Thus, high emissions are registered in grid G5 in both cities which shows the traffic activity and congestion in urban areas.

Table 6: AI Model Performance for Vehicle Detection

AI Model	Accuracy (%)	Precision (%)	Recall (%)
CNN	91.8	90.5	89.6
RNN	88.4	87.1	86.8
YOLO	96.5	95.8	95.2

Analysis

Compared with the test models, YOLO model had the highest accuracy and detection performance. The model was able to effectively estimate vehicle categories through traffic images and video streams successfully; it is applicable for real-time emission inventory applications.

Overall Conclusion

The major contribution of the present study was the successful development of an Artificial Intelligence (AI) based vehicular emission inventory model for Nagpur and Mumbai cities, by combining conventional emission inventory approaches along with advanced machine learning and deep learning approaches. A hybrid approach

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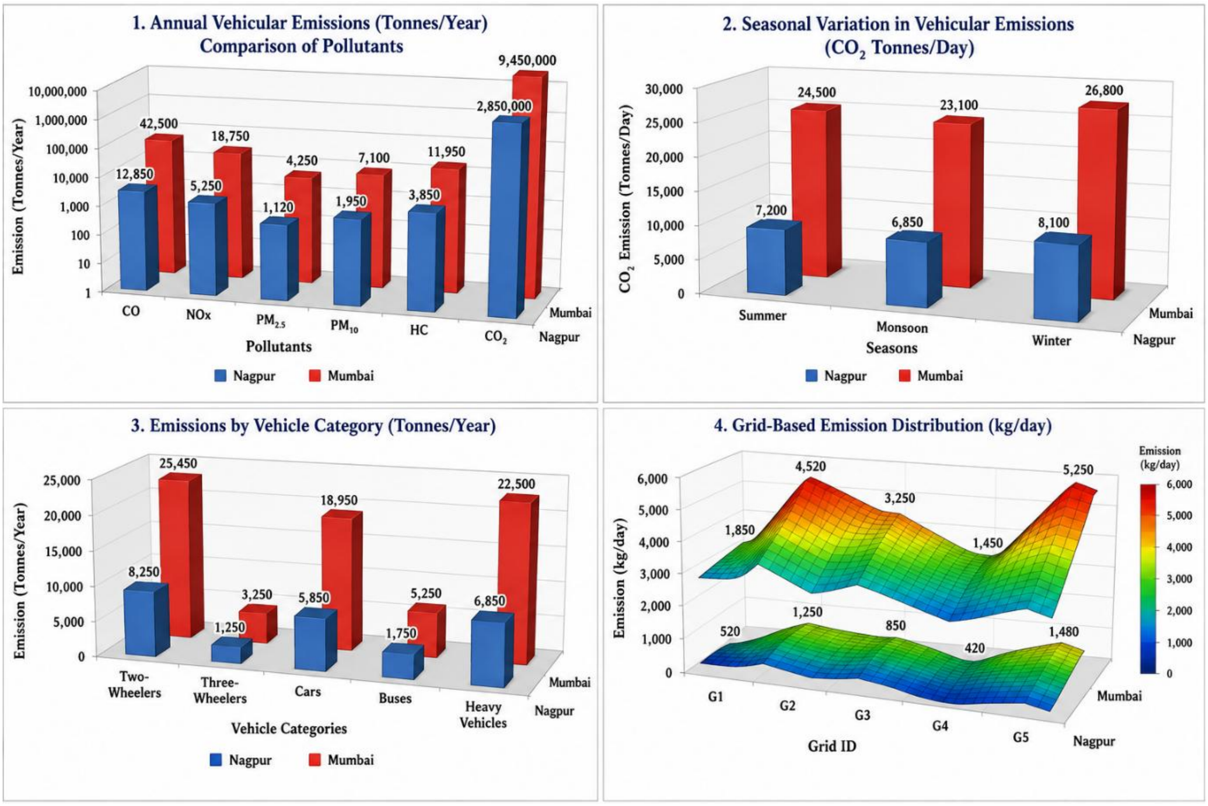
comprising of a bottom-up and a top-down methodology was used for the estimation of vehicles emissions and their spatial and temporal distribution within the urban areas selected for the study.

The results showed a significant difference in the numbers of registered vehicles - there are 5.99 million against 1.81 million for Mumbai and Nagpur respectively. In both cities, vehicles accounted for the majority of the vehicle fleet, with passenger cars making up a significant portion of vehicle emissions, as did heavy vehicles. Emissions of all pollutants (CO, NOx, $PM_{2.5}$, PM_{10}, HC and CO_2) were significantly higher in Mumbai, highlighting the impact of road traffic and urbanisation on air pollution.



The seasonal analysis showed that seasonal vehicle emissions change over time, exhibiting highest emission at winter season and lowest emission in monsoon season. The differences in these variations are caused by variations in meteorological conditions, traffic and atmospheric dispersion. In addition, it showed that even though they have a relatively small population, heavy-duty vehicles and passenger cars are high emitters of pollution.

The obtained spatial analysis with the grid technique was seen to have effectively identified emission hotspots within the study area. The highest emission intensity was measured in Grid G5, showing that the high-traffic areas in cities – such as major transportation corridors, business centres, and busy urban areas - are key emission sources for air pollution. This spatial information can help decision makers and urban planners to plan and implement targeted mitigation and traffic management intervention.

Application of Artificial Intelligence greatly improved the emission estimation process. Compared to the tested AI models, YOLO is the most effective when it comes to real-time vehicle detection and classification from traffic image and video data with an accuracy score of 96.5%. Our findings show that using an AI-based method yield more precise, efficient and scalable emission inventory development solutions than survey-based alternatives.

In summary, the study highlights the power of integrating emission inventory approaches, GIS spatial analysis, and AI techniques to develop a comprehensive framework for evaluating urban vehicular emissions. The built model could be used in designing environmental monitoring, transportation planning and sustainable processes for urban development. In addition, the results highlight the importance of developing cleaner automobiles and application technology, enforcing stricter emission control measures, building a better public transport system,

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and implementing smart traffic management methods to combat urban pollution originated from vehicle exhausts and optimize urban air quality in fast-growing cities.

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