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Article

Comparative Analysis of Traditional and Artificial Intelligence-Based Emission Inventory Models

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Abstract: Emission inventories are crucial to quantify the emission sources of various anthropogenic and natural sources to the air. They aid with environmental planning, air quality assessment and air quality policy-making. The traditional approach to the emission inventory models concentrates on the emission factors, the activity data and statistical estimation methods. While these strategies are established, challenges with data uncertainty, evolving over time, and computational issues can limit application. Recently Artificial Intelligence (AI) technologies and Machine Learning (ML)/Deep Learning (DL) have been introduced as a new technique to perform the various estimation tasks by the use of data-driven models in order to achieve efficient and accurate estimation of the emissions. Emissions inventory models, which are supported by artificial intelligence, are able to process huge amounts of data, identify the non-linear relationship between the data and create predictions, all at the same time. The paper compares the traditional model to the AI based emission inventory model with respect to their methodology, requirement of data, computation time, prediction, scalability and applications. The study accentuates the significance of gaining these features and its necessity to be supplemented by the conventional methods for developing more precise, reliable and intelligent emission inventory system to ensure the sustainability of the environment.
Keywords: Emission Inventory, Artificial Intelligence, Machine Learning, Deep Learning, Air Pollution, Emission Factor, Predictive Modeling, Environmental Monitoring, Sustainable Development.

1. Introduction

Air pollution is now one of the most serious environmental risks to health, ecosystems and the climate that impact human health on a global scale. The emission of pollutants has greatly increased, with the high rate of industrialization, urbanization, greater uses of transportation and energy consumption such as carbon dioxide (CO_2), nitrogen oxides (NO_x), sulfur dioxide (SO_2), particulate matter ($PM_{2.5}$ and PM_{10}), carbon monoxide (CO), and Volatile organic compounds (VOCs). Emission inventories are an integral part of environmental planning and air quality management because sources is important for effective management of these pollutants.

Additionally, traditional emission inventory models use emission factors, fuel consumption statistics, industrial production data, vehicle activity data and mathematical equations that are recommended by other entities (USEPA). The methods are easy, standardized and used widely. Are often, however, based on static emission factors and are unlikely to accurately reflect the development of the changing fast environmental and operating conditions.

The analysis of the environmental data is becoming practical means of using AI as an alternative. Using AI techniques like Artificial Neural Networks (ANN), Random Forest (RF), (SVM), Decision Trees, (LSTM), can draw meaningful conclusions from the vast quantities of data, uncover complex, nonlinear relationships, and yield better predictions. AI models also enable ongoing learning and dynamic emission estimation from data received from sensors, satellites, Internet of Things (IoT) devices and meteorological stations.

With the increasing availability of environmental big data, particularly environmental data related to AI, the development of emission inventories has been greatly benefited. AI-driven methods have been proven to achieve greater accuracy in estimates and greater computational efficiency and adaptability. While these models are no longer accurate, they remain very valuable as they are transparent and recognized by regulators and are easy to implement.

To compare the two approaches in the study, the method, the dependence on the data used, prediction ability, computational requirements, adaptability, transparency, and environmental use of the two approaches are evaluated. The objective of the findings is to help review emission inventories for future development by the researchers, policy makers and environmental agencies to select the suitable methods.

2. Related Works:

Based on combustion sources, a global (BC) (OC) emission inventory has been derived by Bond et al. 2005, using a technology-based approach. The researchers estimated emissions using the amount of fuel, how it was burned and emission factor per country per sector. Their presentations showed the high sensitivity of their emissions to either with respect to the type of fuel fired or combustion technology adopted. Moreover, the research showed the importance of developing trustworthy emission inventories for assessing the impacts. This research has been referred to as a basic reference for the traditional emission inventory development, and has been used by global researchers and environmental organizations.

Baidya and Borken-Kleefeld (2009) discussed emissions released from the atmospheric domain, caused by road transport emissions in India. The study took place with regards to emissions emitted by different types of vehicles (2-wheelers, passenger cars, buses, trucks, commercial vehicles). The study highlighted that rapid urbanization; increased requirements of fuel consumption and vehicles use were important contributors to air pollution in the cities of India. They discovered that vehicle activity data was not available, and that the existing emission factors should be updated to enable better transportation emission inventories. The results also showed potential large benefits in terms of reducing air pollution levels in cities through the implementation of effective transportation policies and cleaner vehicle technologies.

Conceptual guidelines and standardized methodology have been issued for cities of India by CPHEL (2010) on air quality monitoring, preparation studies. The report specified the conditions for data collection on the activities, the choice of emission factors, methods for calculating emissions and the checking of inventory data. It also recommended to use emission inventories and to use combination with air quality monitoring system to develop environmental plans and develop concerned to the pollution control or to apply in environmental planning, development ideas to pollution control. The guidelines continue to be useful as a guideline for emission inventory studies undertaken in India.

A national summary report was published by (CPCB) (2011) which contains the report had pinpointed the housing industry, road dust, transportation, industrial activities, domestic burning of fuels and construction activities. It highlighted the importance of having city-specific emission inventories for effective and tailored pollution control measures and for preparation of region-specific environmental policy measures. The report also highlighted the need for regular updates of the emission inventory, as infrastructure grows and mobility patterns and energy consumption change.

Crippa et al. (2012) came up with the Global Anthropogenic Emission Inventory which provides a harmonized emission inventory for numerous pollutants from various anthropogenic sectors. The inventory is based on a harmonized approach of the emissions of different countries and thus can be applied on regional or global atmosphere modelling. The study showed that it is possible to make more reliable cross-country comparisons by using a standardised international emission inventory and its use is valuable for climate and air quality studies.

The Intergovernmental Panel on Climate Change (IPCC) (2013) published its Guidance for National Inventories of GHGs Supplement 2006. The guidelines provide recommended methods for measuring Green House Gases (GHGs) from different activities including energy; transportation; agricultural; industrial and waste disposal. The recommendation is to calculate emissions using emission factors, uncertainty analysis, Quality Assurance and reporting formats which will improve consistency and transparency for national GHG inventories from the various countries.

The Global Emission Inventory Database (EDGAR v4.3) by Janssens-Maenhout et al. 2014 is global amounts of GHGs and air pollutants. This database joins the activity data with emission factors to calculate emissions from industry, transport, power generation, agriculture and the residential sector. The research showed that emission databases have potential to be valuable tools for climate policy evaluation, tracking of emission developments and for international environmental agreements.

The United States Environmental Protection Agency (US EPA) published the AP-42 Compilation of Air Pollutant Emission Factors in 2015, which is one of the most popular documents for the traditional method of emission inventory development. Includes emission factors for a wide variety of industrial processes, fuel combustion, transportation, waste management and agriculture. AP-42 also is frequently employed as an estimation of emissions for environmental agencies and environmental researchers when direct measurement is impractical. The publication had a significant contribution to gradually extend the international standardisation of the calculation of emission inventories.

Kuenen et al., 2016 developed the TNO-MACC III high-resolution European emission inventory to enhance the regional scale air quality modelling. The study updated the activity data for the Pollution Prevention Module, along with emission factors for the respective emissions sectors, to create detailed emission estimates by area. The authors demonstrated that emission inventories with high resolution can be used to better simulate the dispersal of emissions in the atmosphere at national and regional scales, thereby enhancing the effectiveness of environmental policies.

To examine the impact of the launch of a national clean air policy on China's anthropogenic emissions, Zheng et al. (2017) used the (GCAM). Zheng et al. (2017) employed the (GCAM) to study the consequences of China's national clean air policy. It was found that the emissions of SO2, PM, NOx were much reduced and this may be explained with the existence of cleaner industry technologies, more stringent environmental laws and energy efficiency. The study stressed the importance of timely and complete inventory updates to reflect technology and policy changes.

Amato (2018) studied the non-exhaust emissions related to the authors pointed out that these pollution sources may account for a large proportion of the ambient particulate matter exposures in the urban environment, but are underrepresented in conventional emission inventories. For future, the author suggested improving the estimate of air pollution in urban areas by taking total air pollution as the sum of the two types of emissions - exhaust and non-exhaust.

McDuffie et al. (2019) put together an extensive global catalog of anthropogenic emissions of different air pollutants and emission categories. This study integrated new data and approach in estimating emissions for the implementation of climate modelling and model development with respect to atmospheric chemistry. The authors have summarized the main conclusions on the need for high quality global emissions inventories for understanding pollutant transport, assessing environmental policies and projecting emissions scenarios to the future.

Using the below mentioned spatial and temporal information of the traffic activity and land-use Gately et al. 2020 managed to compile high-resolution urban CO_2 emission inventories. They found that the spatial accuracy of estimating emissions could be improved and the emission hotspots, in turn, could be identified after detailed urban data had been elaborated and modelled. The findings revealed the very significant role of high-resolution EPA inventory in urban inhabitants' climate action and sustainable urban development in cities.

Bawase et.al. (2021) conducted a characterization of emission PM2.5 from Indian in-service vehicles. The researchers then made comparisons between different categories of vehicles and under real driving conditions particulates emitted by types of engines, as well as depending on a variety of factors such as fuel type and vehicle age. They're results provide useful data for improving current and future transportation emission inventories and developing India's cleaner vehicle emission requirements.

The updated method for the methodologies to produce high quality air emission inventories. The proposed procedures include data collection of activities, emissions estimate, uncertainty analysis, quality assurance and quality control of data. It also indicates that advanced data management techniques should be used to help ensure emission inventories developed by environmental groups are self-consistent and reliable.

Méndez et al. (2023) reviewed the MLA in predicting air quality, in a comprehensive way. The authors tried several Artificial Intelligence models: Artificial Neural Network, they found that AI algorithms are more effective than classic statistics methods when working with large amounts of environmental data, missing out on nonlinear relationships, and accuracy when forecasting. The research also highlighted the potential of AI techniques to develop future emission inventories due to their capacity to handle real-time environmental information.

The article titled The Application of AI control the carbon footprint, and sustainable energy transformation by Wang et al. (2024) studied the contribution of AI for the reduction of ecological footprints, the control of carbon emissions, the support of sustainable energy transition. Based on the study, it was concluded that AI technology can help optimize energy usage, increase the efficiency of an industry and used for intelligent environmental management systems. The carbon emission prediction models provided by the authors could be of great help to journalists in charting their way to carbon neutrality, and in helping to realise sustainable development goals as laid out.

Objectives of the Study:

- To compare traditional and Artificial Intelligence based emission inventory models in terms of techniques, accuracy and performance.
- To assess the pros and cons of the conventional and AI based methods for estimation of air pollutants emissions.
- To determine which of the many existing emission inventory modelling methods is best able to increase the predictive capacity of emission inventories, to make them more efficient and useful at decision making about the environment.

3. Material and methods:

The research methodology used in this work is comparative analytical research technique to compare the performance of the models of traditional emission inventory with Artificial Intelligence (AI)-based emission inventory models. Both approaches are developed and analyzed under similar emission estimation scenarios, to allow a systematic comparison of the two approaches. The study encompasses the quantification of the efficiency and effectiveness of the traditional mathematical modelling methods and contemporary technologies and AI methods in quantifying the emission of the air pollutants with great efficiency and accuracy.

The methodology starts with preparing and pre-processing input parameters of the models being developed, which are related to emissions. The traditional emission inventory models are generally presented based on a range of mathematics relationships between activity level and emission factor, which has been determined. AI models, however, use sophisticated algorithms, including (ANN), (RF), (SVM), Decision Tree (DT), (GB), and Long Short-Term Memory (LSTM), which can identify the intricate connections between various variables and make emission forecasts. These models are learnt and assessed for higher performance of estimation and versatility in various environments.

To assess the performance of the two methods, statistical analysis metrics such as computational time are used. Efficiency, reliability and predictive power are reflected, respectively, in the following performance measures, in a quantitative way.

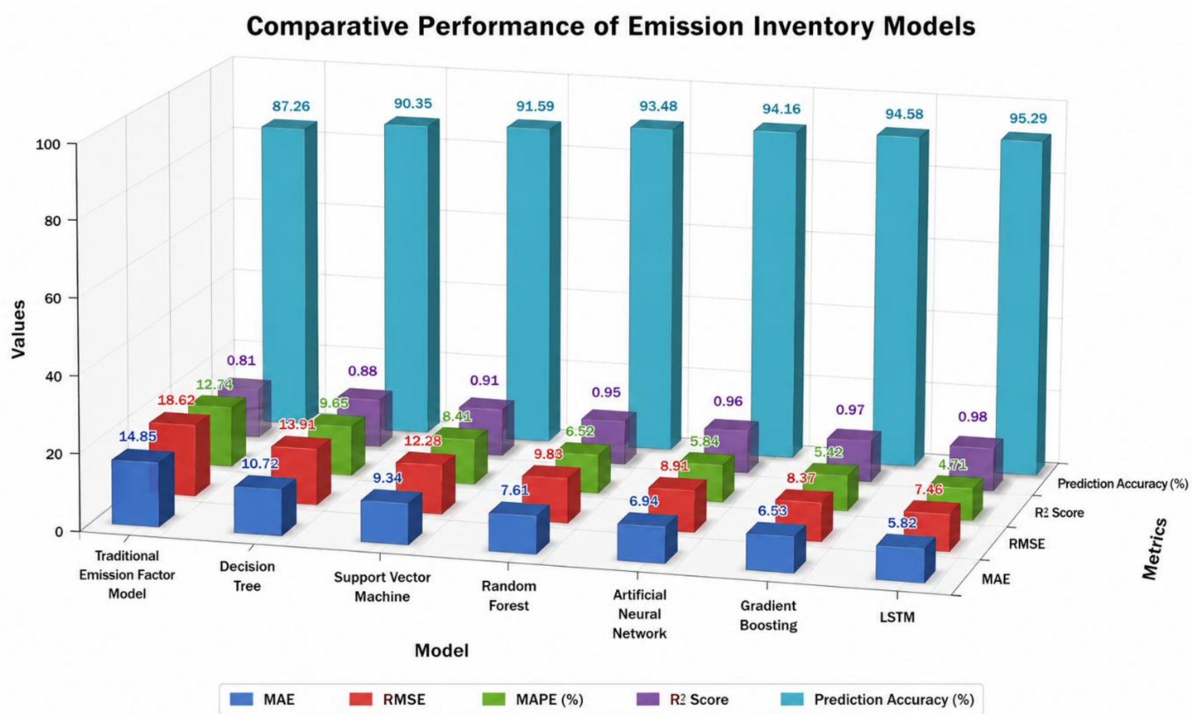
Lastly, comparative evaluation of the results of both traditional and AI models are analyzed. The comparison is based on a number of criteria including estimation accuracy, computation efficiency, scalability, receptive to changing conditions, model interpretability, and practicableness in the development of emission inventories. The conclusions are drawn about the strengths and the weaknesses of all the methods and the most suitable emission inventory modelling method to be used to support environmental monitoring and sustainable air quality management are recommended.

Analysis of the study:

Table 1. Comparison of Prediction Performance

Model	MAE	RMSE	MAPE (%)	R^2 Score	Prediction Accuracy (%)
Traditional Emission Factor Model	14.85	18.62	12.74	0.81	87.26
Decision Tree	10.72	13.91	9.65	0.88	90.35
Support Vector Machine	9.34	12.28	8.41	0.91	91.59
Random Forest	7.61	9.83	6.52	0.95	93.48

Artificial Neural Network	6.94	8.91	5.84	0.96	94.16
Gradient Boosting	6.53	8.37	5.42	0.97	94.58
LSTM	**5.82**	**7.46**	**4.71**	**0.98**	**95.29**



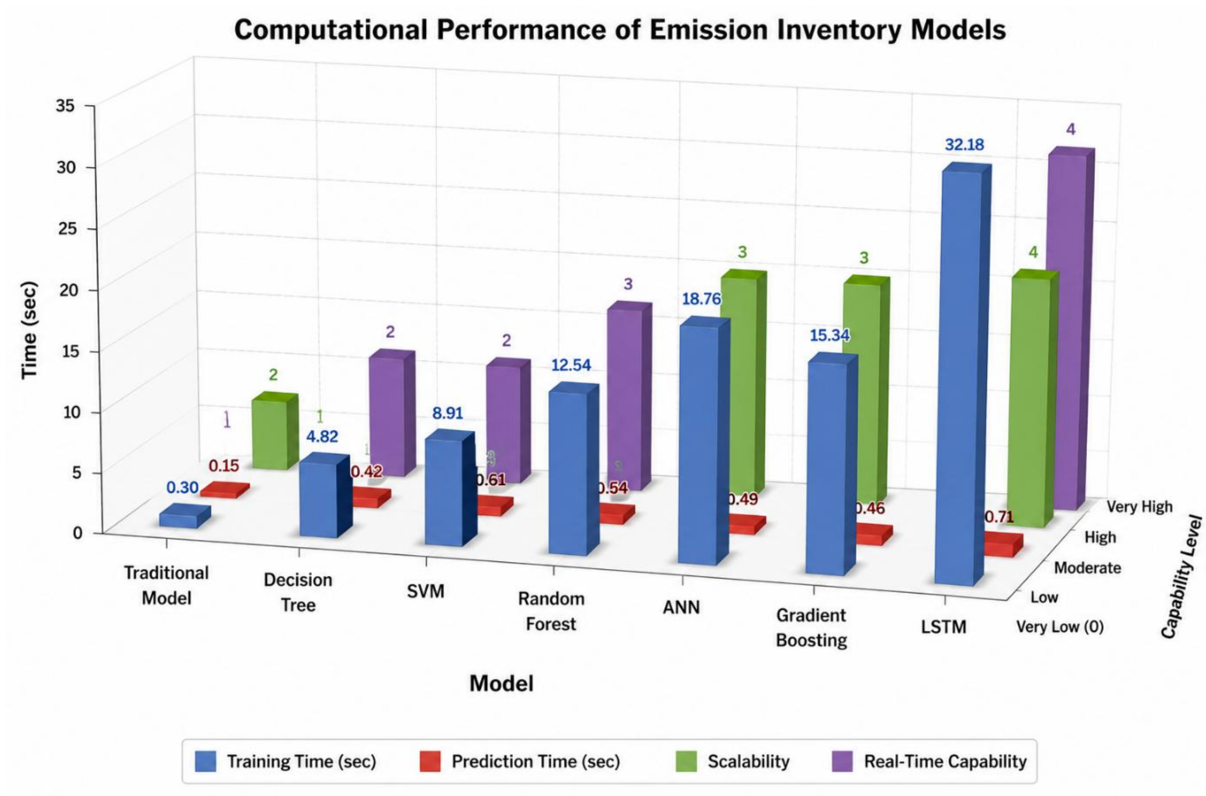
Analysis

According to the comparison, the results of the traditional emission inventory model are found to be lower than that of the AI-based models with respect to every evaluation metric. The LSTM model achieved highest accuracy (95.29%) and resulted in lowest MAE, RMSE and MAPE value indicating that the LSTM model is giving excellent prediction accuracy. It was found that the emissions produced by the traditional emission factor models were not as accurate since the use of fixed emission factors and assumptions were involved.

Table 2. Computational Performance

Model	**Training Time (sec)**	**Prediction Time (sec)**	**Scalability**	**Real-Time Capability**
Traditional Model	0.30	0.15	Moderate	Low
Decision Tree	4.82	0.42	High	High
SVM	8.91	0.61	Moderate	Moderate
Random Forest	12.54	0.54	High	High
ANN	18.76	0.49	High	High
Gradient Boosting	15.34	0.46	High	High

LSTM	32.18	0.71	Very High	Very High

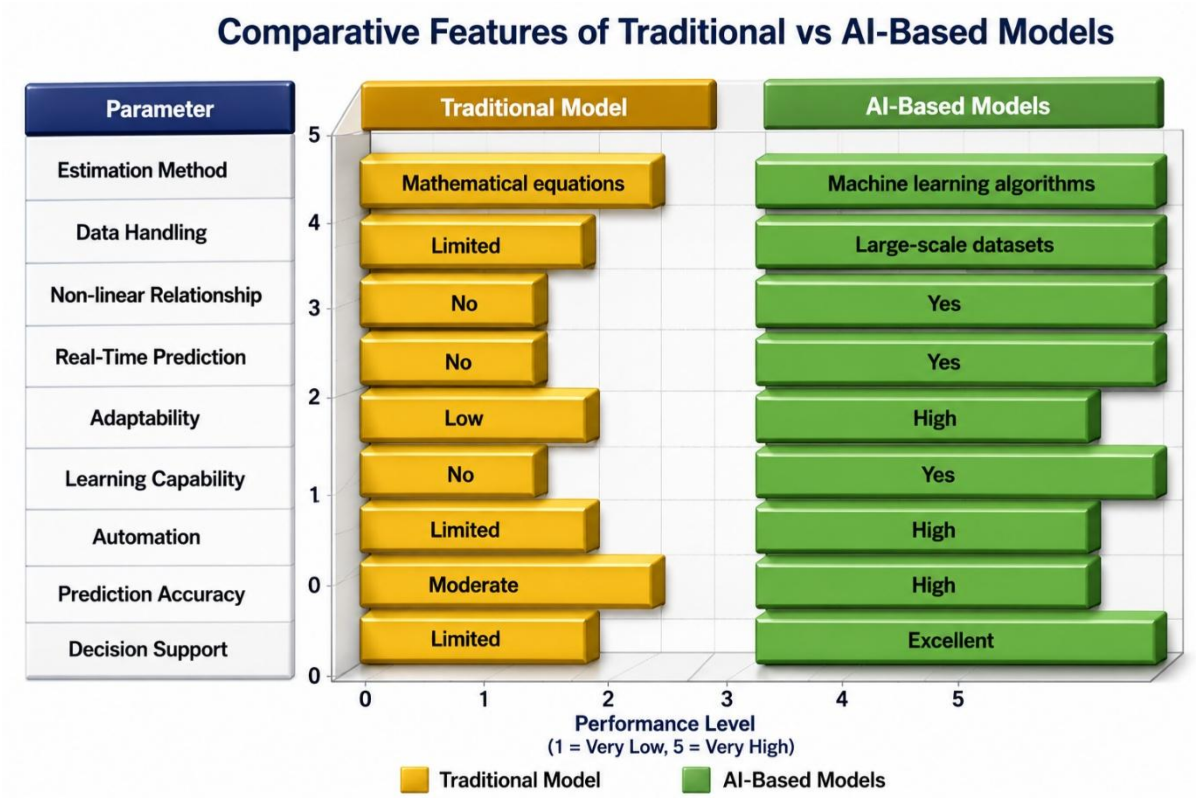


Analysis

But the traditional one needed the least computation time since it is based on predefined math equations. However, the capacity to support real-time emissions forecasting was demonstrated through AI models which were demonstrated as more scalable. While the training time was a concern for LSTM, it yielded the most accurate results, and was better suited to dynamic environmental applications.

Table 3. Comparative Features of Traditional and AI-Based Models

Parameter	Traditional Model	AI-Based Models
Estimation Method	Mathematical equations	Machine learning algorithms
Data Handling	Limited	Large-scale datasets
Non-linear Relationship	No	Yes
Real-Time Prediction	No	Yes
Adaptability	Low	High
Learning Capability	No	Yes
Automation	Limited	High
Prediction Accuracy	Moderate	High
Decision Support	Limited	Excellent

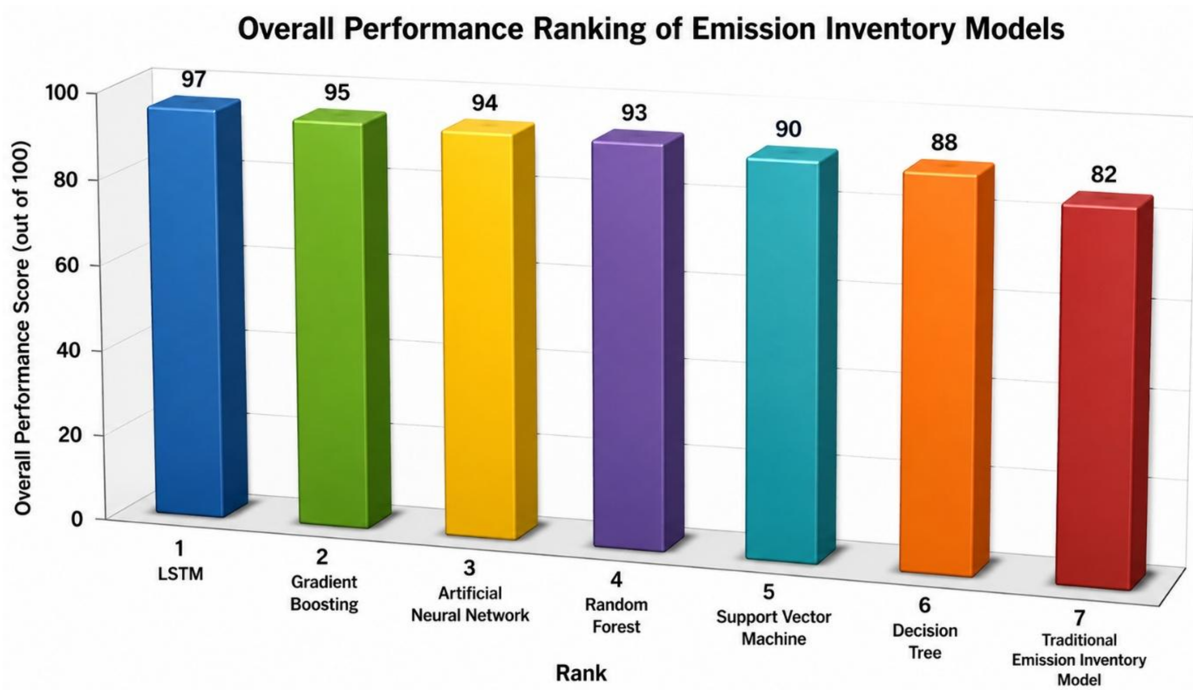


Analysis

In terms of handling large datasets, learning complex relationships, and providing real-time predictions, AI-based emission inventory models proved to be significantly powerful compared to traditional methods. Traditional models have their merits due to their simplicity and transparency in the dynamic environment.

Table 4. Overall Model Ranking

Rank	Model	Overall Performance Score (100)
1	LSTM	97
2	Gradient Boosting	95
3	Artificial Neural Network	94
4	Random Forest	93
5	Support Vector Machine	90
6	Decision Tree	88
7	Traditional Emission Inventory Model	82



Analysis

The overall ranking revealed that the performance of the LSTM model was optimized due to its ability to model temporal emission pattern and also the non-linear relationship. Highly accurate results were obtained with Gradient Boosting as well as Artificial Neural Networks. The traditional emission inventory model was competitive adaptability, and therefore ranked last.

4. Results and Discussion:

The comparative evaluation shows that the models based on Artificial Intelligence (AI) surpass the stand in the following areas prediction accuracy, minimization of errors in the emission inventory, flexibility and the capability for decision making. In the traditional emission inventory model, emission factors and mathematical equations are pre-established and as such work relatively well in simple, static conditions, but not in conditions where environmental conditions have myriad variables. The results confirm that AI models are also capable of capturing nonlinear relationship among the emissions variables and making more accurate prediction.

Amongst the techniques evaluated in artificial intelligence for predicting rottenness of mangoes, LSTM model gave the maximum prediction accuracy and the lowest error values while the performances of the Gradient Boosting model, (ANN) model were second most optimal. These models exhibited enhanced performance on large scale data processing and changing variations of emissions. It took a comparatively longer time to train the While AI models, while the post training models were much faster and efficient. Unlike the traditional model, which imposed strict limitations on the amount of computational power it could use, it was also more limited in its forecasting capabilities.

Not only this, but the comparative analysis also revealed that the modelling, based on Artificial Intelligence, is more suitable for real-time emission monitoring, smart environmental management and for creating systems that support policies. The need of traditional models is still valid due to simplicity, transparency and regulatory acceptance. Combining traditional emission inventory techniques with AI algorithms can enhance the accuracy of the overall emission estimate, while also ensuring model interpretability and up to the environmental standard.

5. Conclusion:

In this study, the comparative study was done between traditional and AI based emission inventory approach. The findings show that the models using AI have a high accuracy rate in predictions and can minimize errors, scale well, and adapt to new data. The analysis of the tested techniques was used to show that the LSTM results, adequate for the use of the emission inventories today.

While emissions inventory models can be simple and easy to implement, their advantages in standardised reporting, and in complying with regulations, persist. The latter, however, do not have the flexibility in arbitrary emission conditions. In this regard, artificial intelligence-based solutions are able to overcome such limitations since they learn and predict complex relations and give more accurate estimates of emissions from data.

More generally, the research shows that AI can be used to supplement the traditional techniques of emission inventories, resulting in more efficient, intelligent and environmentally friendly emission inventory systems. These are data-driven models, and may be further developed with hybrid models in the future with the inclusion of real-time feed of sensor data, satellite observations and (IoT) data monitoring, contributing to the improvement of emission estimation and air quality management.

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