

Enhancing Emitter Prediction in Heavy Duty Vehicles Using Recurrent Convolutional Neural Network

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Abstract:

Predicting emissions from Heavy Duty Vehicles (HDV) accurately is crucial for environmental monitoring and regulatory compliance. These vehicles, particularly diesel trucks, significantly contribute to urban air pollution, Particulate Matter (PM), and Nitrogen Oxide (NOx) emissions. Effective vehicle emissions control and detection are crucial for protecting public health. Regular vehicle inspections typically conducted every six months or annually, aim to identify and filter out high-emission vehicles at testing stations. This research compares the performance of Faster Mask Recurrent Convolutional Neural Networks (FMRCNNs) to existing in predicting vehicle emissions, aiming to improve prediction accuracy and enable more effective monitoring and control. This study presents a novel approach using FMRCNN that leverages convolutional layers for spatial feature extraction and recurrent layers for modeling temporal dependencies. The FMRCNN model is thoroughly evaluated against CNN and LSTM models using a comprehensive dataset of heavy-duty vehicle emission measurements. The results show that the FMRCNN model significantly outperforms CNN and LSTM models in prediction accuracy and computational efficiency, making it a superior choice for emission prediction tasks. These findings demonstrate the potential of FMRCNN to improve emission predictions for HDV, providing a more accurate and reliable tool for environmental monitoring and helping to ensure compliance with regulatory standards. FMRCNN can reduce harmful emissions and promote a cleaner environment by enhancing emission prediction capabilities.

Keywords: Emission Prediction; HDV; Fast Mask Recurrent Convolutional Neural Network; Regulatory Compliance; Temporal Dependency Modeling; Temporal Dependency Modeling ; Prediction Accuracy; Computational Efficiency.

1. Introduction

Vehicle emissions contain toxic pollutants and harmful greenhouse gases, contributing to pressing issues like ecological damage and poor air quality. In India, regional atmospheric problems are worsening, and HDV significantly impacts air quality. As a result, NO_2 is widely regarded as a marker of road traffic pollution. Furthermore, NO_2 undergoes additional atmospheric reactions in the presence of oxidants like O_3 , leading to the formation of nitric acid and sulphuric acid [1]. These secondary pollutants significantly contribute to the production of nitrates, sulphates, and organic aerosols, which are major components of PM_{10} and $\text{PM}_{2.5}$. Therefore, identifying and addressing high-emitting vehicles through repair or deregistration can effectively reduce vehicle pollutant sources and improve urban air quality. The rapid urbanization growth has led to pressing environmental concerns in the transportation sector, significantly contributing to climate change [2]. Recognizing the socioeconomic impacts of shipping, such as the consumption of energy and pollution in the air, depends on precise estimation and visualization of the consumption of fuel and emission levels. Creating efficient emission reduction strategies requires this knowledge. Consequently, there is a global surge in interest in practical studies among scholars and engineers, who are utilizing data analysis and machine learning to advance conservation and lessen the negative ecological effects of transportation [3]. To calculate the expense of energy and pollutants in the atmosphere resulting from transport and outlining emission mitigation strategies, it is essential to estimate and visualize the consumption of fuel and exhaust emission levels [4]. Since climate change has been a major concern in the last ten years, estimating models of CO_2 emissions and consumption of fuel for automobiles has become more and more important. As a result, academics and engineers throughout the world are becoming increasingly interested in practical studies for sustainability (particularly in the fields of statistical analysis and computational training) [5].

Concern over the effects of global warming has grown over the past few decades due to raised Greenhouse Gas (GHG) emissions. 75% of all CO_2 emissions from ecological activities are produced globally by mobility [6]. As a result, reducing transportation-related emission levels is a global goal in the fight against warming temperatures. When taking into account the economy, society, and environmental goals, it is crucial to evaluate urban roadways and contact with pollutants released from motorized congestion, particularly in growing nations [7]. The way that cars release CO_2 is seen in Figure 1.

Any economic growth must build up its means of travel facilities, including highways and freeways that connect towns. The fast growth of infrastructure necessary to support the emergence of new mobility options has resulted in congestion on the country's roadways. As a result, there has been a noticeable deterioration in the air quality near highways, junctions, and toll ways. The main source of emissions from traffic, including Carbon Monoxide (CO), is vehicle exhaust. These emissions account for a significant portion of the total air pollution these facilities create [8]. It can assess and replicate the impacts of vehicular emissions on road ways, spatial forecasting techniques are an excellent tool for supporting decision-making.

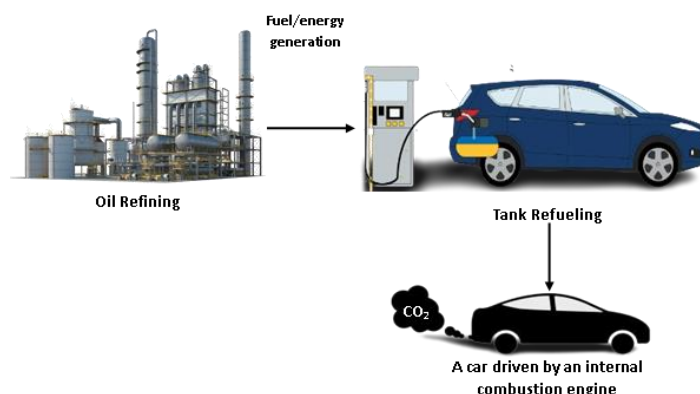


Figure 1: Car releasing emitting CO₂

Excessive traffic volume can lead to several negative effects such as an upsurge in noise and gaseous pollutants. Exposure to elevated CO₂ levels has been linked to a notably higher risk of developing several illnesses and ailments in humans including cardiovascular disease, cancer, breathing problems, and premature births [9]. At Vehicle Inspection Stations (VISs), where tailpipe emission information is examined and assessed to find high-emission transportation sources that need to be periodically checked for their emissions status, cars are now required to be examined for emissions from the exhaust at VISs once every six months or once a year [10].

After gathering RDE information from hybrid electric cars and evaluating the precision of many machine learning algorithms to predict carbon dioxide emissions, concluded that the Gaussian technique for extraction method is particularly efficient. Furthermore, the pace at which hybrid electric cars accelerate has not always resulted in a corresponding rise in CO₂ emissions. Artificial Neural Networks (ANNs) have been used extensively in the literature over the past few decades as a technique for highly accurate number estimation in everyday situations [11]. Using the characteristics of axle velocity, acceleration, and corresponding derivatives, constructed an ANN model to accurately forecast CO₂ emissions from heavy-duty diesel vehicles. ANN has been used to forecast the contaminants emitted while a vehicle's emissions burn in a few experiments [12].

2. Related Works

Identifying high-emitters can be viewed as a binary classification problem, where emissions are categorized as normal or abnormal. By incorporating a temporal dimension, this problem can be reframed as the time-series anomaly detection task. These classical methods provide a foundation for detecting anomalies in emission patterns. Anomaly detection methods vary depending on the data, with most approaches relying on statistical features to identify outliers [13]. The supplementary materials provide a comprehensive overview of the main research in this field. The sequence of consecutive values that are anomalous, Point anomalies: individual values that significantly deviate from high-density regions, Contextual anomalies: data points with significant differences from their surrounding values, both before and after, indicating a notable change in the time series pattern. These categories help refine the approach to anomaly detection in time-series data. Specifically, in the task of identifying high-emission vehicles, we concentrate on detecting consecutive periods of abnormal emissions (contextual anomalies), as this is of greater practical significance and relevance [14]. A time series with no variations shows information obtained from a single source that is

connected to the observing period. Any multivariate detection of anomalies technique's effectiveness is greatly influenced by the configuration of the underpinning system that is being observed. While continuous temporal information is frequently accessible in several application domains, exhaust gas monitoring instruments are primarily stationary and positioned on driving roads in the research of emissions from mobile sources of pollution [15]. It is challenging to carry out emission investigations over an extended length of time since these instruments can only gather immediate information when the vehicle passes past. Investigation's experimental information came from OBDs, which can collect live monitoring information about specific automobiles in real time, overcoming the fixed detectors' geographical and temporal constraints and enabling us to do investigations depending on the vehicles' continually updated emission information [16].

After gathering RDE information from hybrid electric cars and evaluating the precision of many artificial intelligence algorithms to predict CO₂ emissions, concluded that the Gaussian procedure for extraction method is the most efficient. The pace at which hybrid electric cars accelerate has not always resulted in a corresponding rise in greenhouse gas emissions. ANN have been used extensively in research over the past few decades as a technique for highly accurate number estimation in everyday situations [17]. Using the characteristics of axle acceleration, torque, and corresponding derivatives, constructed an ANN model to accurately forecast CO₂ emissions from heavy-duty diesel-powered vehicles. An ANN model plus a vehicle dynamics simulation were integrated to predict the short-term greenhouse gas emissions of light-duty diesel vehicles. Engine velocity and torque are the only two factors used in the CO₂ calculation; real driving circumstances are not taken into account [18]. ANN has been utilized in certain research is to forecast the contaminants emitted during vehicle exhaust burning. The issue with these studies is that the models that were utilized to generate the projections took into account just the state of the road and the car's engine at the time. There is a significant time dependency on emissions from vehicles. Time error persists in the calculation between the engine's operating quantity and the exhaust gas value even after time realignment. Humans are unable to rely only on this research to make predictions based on data that is now publicly accessible [19].

To predict transportation-related CO₂ emissions, a variety of models may be employed to describe these various approaches. The foundation of early traffic CO₂ modeling is laid by conventional methods that primarily rely on data sampling and technological tools like GPS. Combining various themed images with vehicle emission formulae can simulate the distribution of traffic emissions in an area and provide instructive maps that can help with decision-making [20]. Newly developed techniques for land-use regression evaluation mostly rely on statistical and soft-computer techniques. Various traffic and road layout-related parameters may be used as inputs in these analytical and mathematical approaches [21].

These models rely on the local setting, which takes into account variables like the kind and brand of the vehicle and the weather. A technique has been developed for identifying the elements of road geometry using surveyed positional information collected from cars as an information source. However, our results are contradicted by the forecasting approach, which only incorporated data about the times at which the Internal Combustion Engine (ICE) cars switched on. Failed to take into consideration variations in the power train's state that arise at high voltages [22]. The influence of

noisy information within the input information, which can lower the accuracy of the model by up to 30%, was also looked at by the authors. While conventional macro and micro approximation methods are utilized in other contexts, several artificial intelligence methods to predict the CO₂ emission rate of hybrid automobiles. The results of the present batch of pollution models are inconsistent; the researchers concluded that there is a problem with them. This problem is caused by the variable CO₂ emissions of hybrid vehicles. The findings of this study provide an important boost to the effort to find a solution to this problem [23].

The intrinsic volatility and disequilibrium associated with traffic patterns and weather factors result in considerable non-stationary and nonlinear features in vehicle exhaust emissions. There are several challenges to precise long- and short-term motor vehicle exhaust emissions forecasting, such as the complex nonlinear relationship and long- and short-term time reliance on different emission gases, such as CO. A novel hybrid deep learning architecture that combines LSTM and BiLSTM algorithms to effectively anticipate multivariate exhaust emissions from vehicles over both short and long periods. This will enable us to get past the difficult obstacles that have been put in our path. There are two main types of vehicle emissions: those that are responsible for global warming and those that are harmful to human health and air quality [24]. A crucial first step in decarbonising the industry of transportation is the use of electric cars. However, according to projections from the Energy Agency of the United Nations, for efforts to keep the temperature rise below 2 °C by 2030, at least 20% of all motorized automobiles (or around 300 million cars) must be driven by power [25]. To determine the research gap, the present techniques that have been employed by various investigators are outlined in this literature review, along with the frameworks and methodologies that have been employed for every methodology.

3. Proposed System

Predicting emissions accurately is crucial for effective environmental monitoring and meeting strict regulatory requirements. Conventional models like CNNs and LSTMs struggle to capture the intricate spatial and temporal patterns in emission data, highlighting the need for improved modeling approaches. This article investigates the use of FMRCNN to improve HDV emission forecast effectiveness and precision. This work is motivated by the pressing need to enhance HDV emission forecasting techniques. The intricate relationships between several elements impacting emissions, which include the speed of the vehicle, pressure, temperature of the engine, and driving circumstances, are difficult for current techniques to simulate effectively. Furthermore, achieving higher forecast accuracy frequently comes at the expense of greater computer complexity, making real-time applications impracticable. Models that are computationally effective and competent to produce precise predictions are desperately needed. By utilizing the advantages of FMRCNN — which blends the temporal dependency modeling of LSTMs with the spatial characteristic extraction powers of CNNs—this work seeks to overcome these issues.

3.1 Dataset preparation

An organized summary of the dataset attributes that are normally gathered and examined to forecast emissions from HDV is given in Table 1. A measurement instance is represented by every line, and a particular aspect or attribute about the automobile or the surrounding circumstances throughout

measurement time is represented by each column.

Table 1: Dataset description

Feature	Description	Type
Vehicle ID	Unique identifier for each heavy-duty vehicle	Categorical
Timestamp	Date and time of emission measurement	Temporal
Vehicle Speed (km/h)	Speed of the vehicle at the time of measurement	Numerical
Engine Load (%)	Percentage of maximum engine load	Numerical
Engine Temperature (°C)	Temperature of the engine coolant	Numerical
Ambient Temperature (°C)	Ambient temperature during the measurement	Numerical
NOx Emission (g/km)	Nitrogen Oxide emission rate per kilometre	Numerical
PM Emission (g/km)	Particulate Matter emission rate per kilometre	Numerical
Acceleration (m/s ²)	Vehicle acceleration at the time of measurement	Numerical
Road Gradient (%)	The gradient of the road surface	Numerical
Weather Condition	Weather conditions during the measurement	Categorical
Road Type	Type of road (e.g., highway, urban road)	Categorical
Driver ID	Identifier for the driver	Categorical

3.2 System Model

For every one of the 600 examples, contour plots of many scalar fields were analyzed to provide testing and training data sets for the FMRCNN algorithm shown in Figure 2.

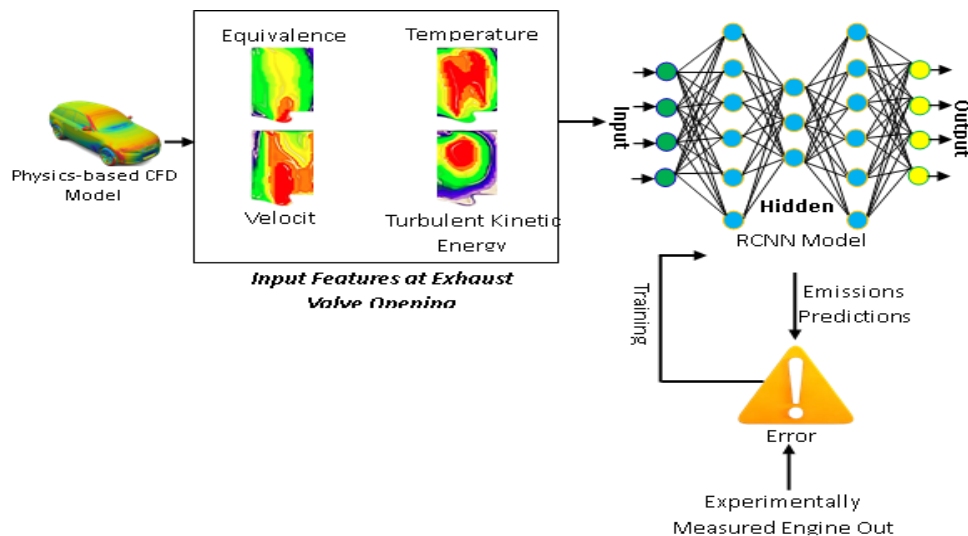


Figure 2: Process overview for developing predictive FMRCNN models

Four viewports, every showing an individual scalar on the vertical cut plane passing through the center of the cylindrical form, made up every processing image. In each example, just one image

went through processing right before the Exhaust Valve Opened (EVO). The environment's temperature and equivalency ratio were included because of their established relationships with emissions while average velocity magnitude and TKE were taken into consideration to take into consideration flow motion's role in creating extra species oxidation consequences that follow EVO but are not directly simulated by the CFD model. The division between contour levels was marked using a banded color system. With red denoting a "high" value and gray denoting a "low" value, every example employed the same absolute scale, meaning that the contour values were consistent.

Owing to the limited information set, a FMRCNN system was constructed using the structure of VGG16 based on the ImageNet dataset in place of building CNN. For this dataset, the convolutional basis of the baseline VGG16 model was kept; the highly connected classification layers was eliminated, and a fully interconnected regressor was added, as seen in Figure 3.

Through the process of preserving the convolutional core during learning and adjusting the hyperparameters of the entirely connected regressor, the weights that were learned of the VGG16 convolutional foundation on the ImageNet dataset were preserved in this investigation. Several combinations of the best models discovered during the hyperparameter optimization process for the regression operator were examined rather than relying on one model to be examined. In the initial training collection (500 images), an ensemble of the top three and five algorithms were examined using continuous five cross-validations.

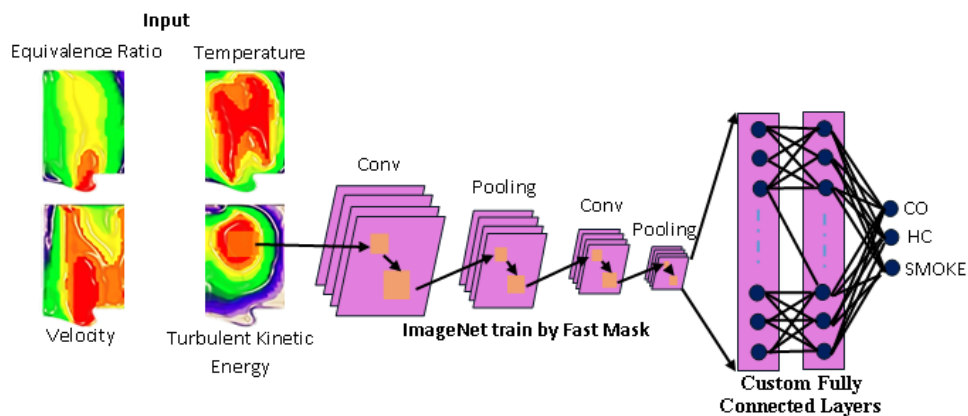


Figure 3: Enhanced image using FMRCNN

Conceptual and analytical consumption of fuel analyses are the two groups into which the vehicle fuel efficiency analyses are divided. While the mathematical fuel utilization model convergence occurs, the mathematical characteristics of automobile movement and fuel consumption information, which includes speed and acceleration, the conceptual fuel spending simulation focuses on the vehicle's operating characteristics, including output power and engine configuration. relative error of less than 10% is constructed by gathering driving behavior data from users' cell phones. Major indications for estimating gasoline consumption include the median acceleration and deceleration, accelerated duration %, deceleration time percentage terms, and floating time percent. The gasoline expenditure was accurately predicted by the model, which had an inverse root average variance of 2.43.

The EDAR device utilizes the technology of on-road remote sensing to measure vehicle emissions in real-world driving conditions shown in Figure 4. The device is installed at a height of 5 meters above the road surface, alongside other instruments such as an automatic number plate recognition (ANPR) camera and a weather station, to collect comprehensive data on vehicle emissions and related factors. Dial has been widely reported to offer superior sensitivity, selectivity, and stability compared to other techniques used in various Vehicle Emissions Remote Sensing Systems (VERSSs). EDAR directly measures NO and NO₂ emissions, providing accurate NO_x values. Additionally, EDAR offers improved particulate matter (PM) measurements compared to other VERSSs and has shown good agreement with emission measurements from Portable Emissions Measurement Systems (PEMS).

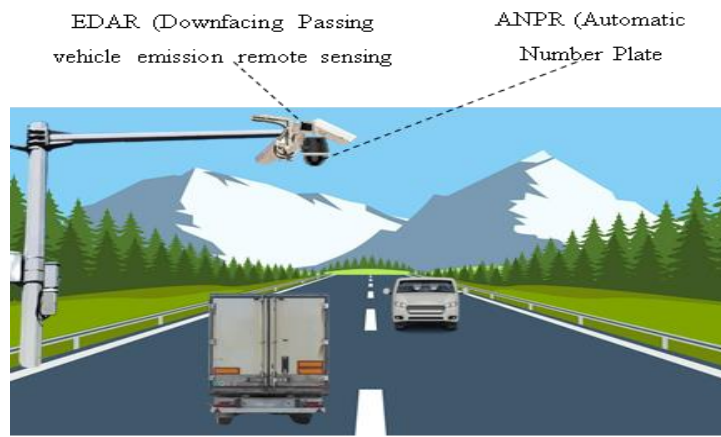


Figure 4: EDAR and ANPR used in proposed system

Calculations:

Convolutional Layers: Apply convolutional filters to capture spatial dependencies

$$\text{Conv}_i = W_i * I + b_i \tag{1}$$

where W_i is the filter, I is the input, and b_i is the bias term.

Masking Layer: Apply masking to handle missing data and emphasize relevant features.

Recurrent Layers (LSTM): Capture temporal dependencies in sequential data.

Input Gate:

$$x^{(t)} = \sigma(W_{xi}i^{(t)} + W_{xh}h^{(t-1)} + W_{xc}c^{(t-1)} + b_x) \tag{2}$$

Forget Gate:

$$f^{(t)} = \sigma(W_{fi}i^{(t)} + W_{fh}h^{(t-1)} + W_{fc}c^{(t-1)} + b_f) \tag{3}$$

Output Gate:

$$o^{(t)} = \sigma(W_{oi}i^{(t)} + W_{oh}h^{(t-1)} + W_{oc}c^{(t-1)} + b_o) \tag{4}$$

Cell State Update:

$$c^{(t)} = f^{(t)} \odot c^{(t-1)} + x^{(t)} \odot \tanh(W_{ci}i^{(t)} + W_{ch}h^{(t-1)} + b_c) \tag{5}$$

Hidden State Update:

$$h^{(t)} = o^{(t)} \odot \tanh(c^{(t)}) \tag{6}$$

Step 3: Training Process

Loss Function: Mean Squared Error (MSE) or another suitable regression loss function.

$$L = \frac{1}{N} \sum_{x=1}^N (\hat{j}_x - j_x)^2 \tag{7}$$

where \hat{j}_x and j_x are the predicted and actual emissions, respectively, for the x-th sample.

4. Results and Discussions

100 images from the experimental set also known as the held-out information were used to assess the model across all emissions species (CO, HC, and smoke) on the test set. Figure 5 compares the projected values of all three emission species (CO, HC, and smoke) by FMRCNN combination models for the tested set with the real (through experiments observed emissions information). In terms of forecasting all three emissions species, the FMRCNN combination model fared better than the most advanced CNN and LSTM models. When contrasted with the most recent forecasts made by the CNN and LSTM models, an important rise in prediction precision ($R^2 > 0.82$) was seen, particularly for unburnt HC and greenhouse gas emissions. To calculate the inputs to the FMRCNN, it needs a low-fidelity chemistry simulation. The capacity to estimate engine-out emissions of cigarette smoke, unburned hydrocarbons (HC), including carbon monoxide (CO) with excellent precision is essential for speeding the development of higher-efficiency engines that meet emission laws shown in Figure 6. This work shows that engine-out emission may be reliably predicted by combining machine learning and physics-based models. Engines powered by gasoline or diesel can use the approach described in this study. The proposed FMRCNN results in computing savings, quicker engine modeling completion times, and far more precise engine-out emission estimates.

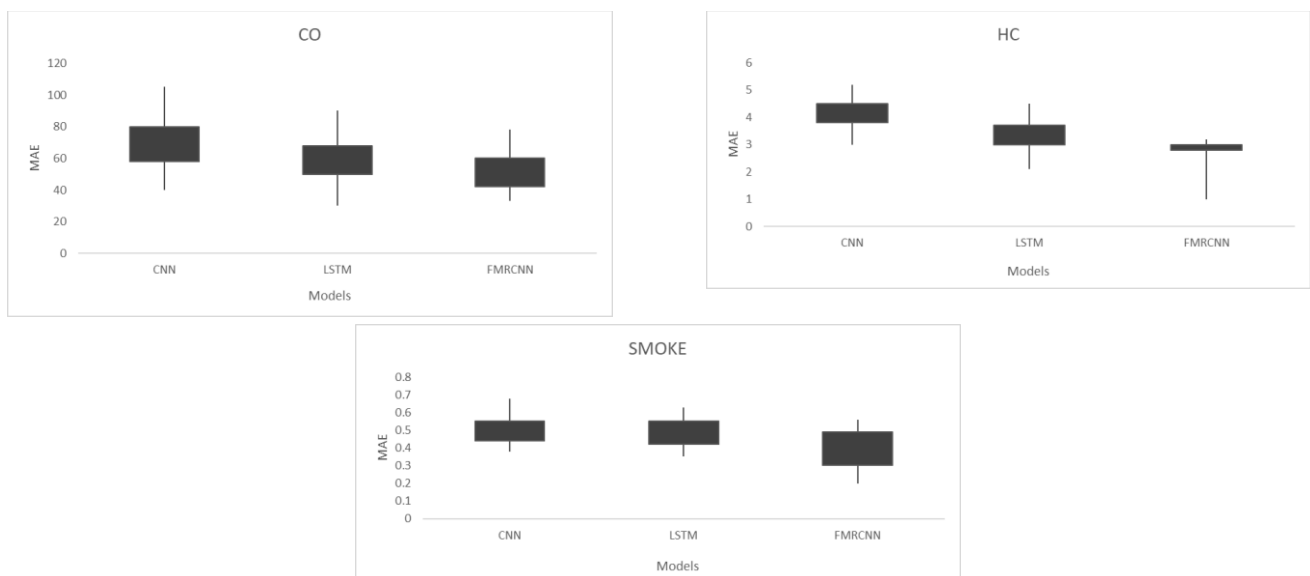


Figure 5: The data set for training (500 photos) using periodic cross-validation methods

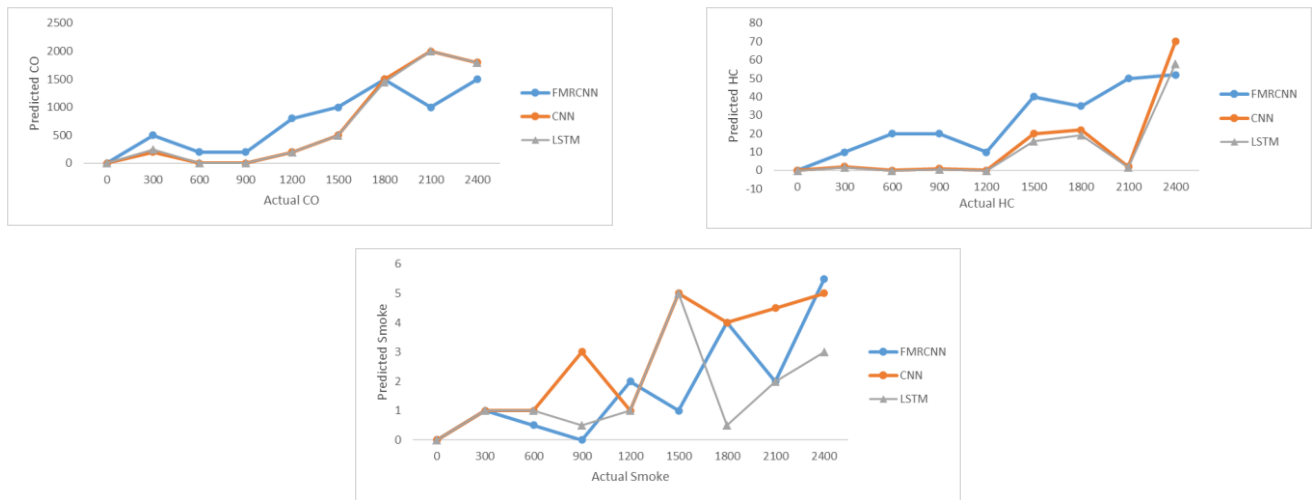
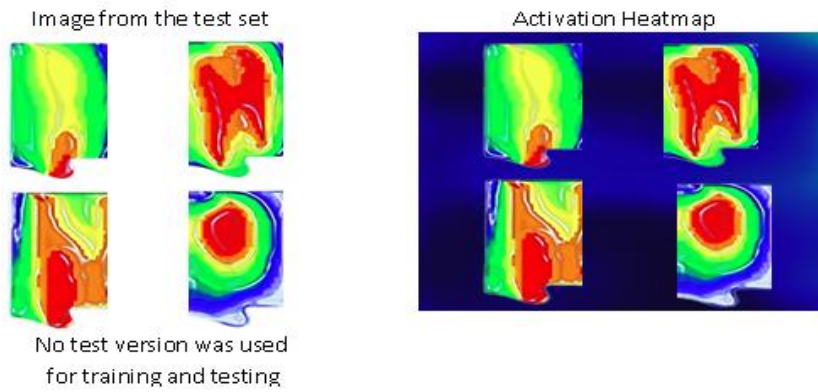
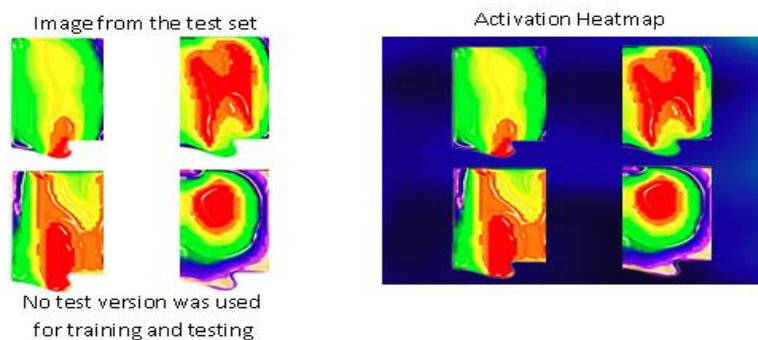


Figure 6: Comparing the CO, HC, and emissions of smoke projected by FMRCNN, CNN LSTM on the experimental set of 100 photos



Prediction of this image			
Actual HC	FMRCNN	CNN	LSTM
2.32	3.8	3.5	4.0



Prediction of this image			
Actual HC	FMRCNN	CNN	LSTM
4.84	5.25	4.2	0.098

Figure 7: Activation heatmaps of two sample images from the test set when predicting HC emissions

Several factors and comments may be made while evaluating the effectiveness of community models in comparison to the single customized model utilizing frequent cross-validation on a 500-image training dataset. In the field of machine learning, FMRCNN synthesizes assumptions from several independent models to yield greater accuracy and reliability of outcomes than any one model could. This method uses model diversity—using distinct methods, information subsets, or model parameter changes, for example—to reduce biases and enhance applicability shown in Figure 7. Repeated cross-validation is dividing the dataset into many folds and utilizing every fold as a confirmation and training set numerous times. It works especially well with smaller datasets, such as the 500 photos stated. By averaging performance measures over multiple information splits, this method aids in the more thorough evaluation of systems and yields a more accurate indication of the usefulness of the framework. Depending on the unique features of the dataset, available computing power, and the intended trade-off between model complexity and performance stability, ensemble models or a single optimal model should be chosen. Ensemble approaches combine the advantages of several models to improve prediction reliability and precision, they often perform better in a variety of circumstances, such as image classification with sparse data. Analysts can visually assess which aspects of the input data are most important to FMRCNN when they superimpose these activation heat maps over the initial version images. This interpretation aids in confirming the actions of the model and pointing out any biases or misunderstandings of visual signals. All things considered, activating heat maps offers a user-friendly way to comprehend and analyze the inner workings of FMRCNN models when used for challenging tasks like forecasting emissions like HC from visual data, increasing openness and confidence in AI-driven environmental tracking systems.

Table 2: Performance measures

Model	Accuracy	Precision	Sensitivity	Specificity	F1-Score
FMRCNN	0.86	0.88	0.83	0.89	0.85
CNN	0.81	0.83	0.79	0.83	0.81
LSTM	0.79	0.81	0.76	0.81	0.78

FMRCNN combines the parallel modeling prowess of RNNs (like LSTM) with the spatial feature extraction skills of CNNs. FMRCNNs are good at capturing both spatial and temporal patterns, they often score well on all measures. CNN does not take time relationships into account and concentrates only on extracting spatial features from data. It often does well in problems where spatial relationships are important, but it might not perform as well in situations that call for sequential knowledge. The LSTM model is ideal for jobs where time structure is crucial since it focuses on modeling sequential data and capturing long-term dependencies. When compared to FMRCNNs, its performance metrics are often more modest, particularly for applications where spatial data is equally crucial. These metrics offer a comparative analysis of the performance of each model type in terms of several elements of prediction accuracy and dependability, showing the advantages and disadvantages of every model type in particular situations shown in Table 2.

Table 3: Performance measures

Model	MAE	RMSE
FMRCNN	0.16	0.21
CNN	0.26	0.31

LSTM	0.21	0.26
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Achieves lower MAE and RMSE than CNN and LSTM because it can efficiently collect both temporal and spatial data. These metrics offer an unbiased review of the prediction error performance of every approach type, showing the advantages and disadvantages of every in various uses, such as image processing and time sequence forecasting shown in Table 3.

Table 4: Training and Validation accuracy

Model	Training Accuracy	Validation Accuracy
FMRCNN	0.96	0.86
CNN	0.91	0.81
LSTM	0.89	0.83

Training accuracy is a measure of how well an algorithm fits its training information, based on its performance on a training set of data. Validation accuracy is an estimation of the model's ability to generalize to previously unidentified information based on the model performance on the different validation datasets (or an evaluation split of the learning dataset). FMRCNN can efficiently collect both time and location data, it often maintains outstanding training accuracy. Generally, validation accuracy ranges from moderate to high, indicating strong generalization ability shown in Table 4.

Table 5: Training and Validation loss

Model	Training Loss	Validation Loss
FMRCNN	0.16	0.26
CNN	0.31	0.36
LSTM	0.26	0.31

Table 5 shows the corresponding advantages and appropriateness of every model type for different information kinds and tasks, giving a summary of the way every modeling type performs in terms of loss throughout both the training and validation loss.

5. Conclusion and Future Enhancement

Enhancing emitter prediction in heavy-duty vehicles through the application of FMRCNN marks a significant leap forward in the realm of predictive analytics for environmental impact assessment. By integrating the spatial feature extraction capabilities of FMRCNN with the sequential learning prowess excels in capturing the complex interplay between driving conditions, engine dynamics, and emission outputs. This hybrid model architecture enables FMRCNN to leverage spatial information from sensor data alongside temporal dependencies over time. This approach not only enhances the accuracy of predicting emissions like CO, HC, and smoke but also provides deeper insights into the underlying factors influencing emission variations. By effectively modeling the intricate relationships within emission datasets, FMRCNNs empower stakeholders in the transportation sector with precise tools for regulatory compliance, operational optimization, and environmental impact mitigation strategies. Looking ahead, ongoing advancements in FMRCNN technology, coupled with broader data availability and refined model training techniques, hold promise for further enhancing predictive capabilities and operational efficiencies in heavy-duty vehicle emissions management. Continual research and development efforts are crucial for optimizing model performance and

extending its application to emerging challenges in sustainable transportation and environmental stewardship. FMRCNNs represent a transformative approach in enhancing emitter prediction for heavy-duty vehicles, underscoring their pivotal role in driving innovation towards cleaner, more sustainable transportation solutions.

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