# A Data-Driven Ensemble Deep Learning Approach to Urban Air Quality Prediction and Management

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Publication Date: 2025/12/23

Abstract: Air pollution has been steadily increasing throughout a number of nations over the course of the last several decades as a direct result of human activity, urbanization, and industrialization. Deep Learning (DL) and Machine Learning (ML) approaches have made significant contributions to the development of methodologies in a variety of areas, including the prediction, planning, and uncertainty analysis of smart cities and urban progress in the present situation. As a result of the fast development in both population and industry, a significant number of major cities have experienced severe air quality (AQ) problems. This research offers a system that is based on ensemble deep learning and was built for the purpose of forecasting the levels of air pollution in smart environments. For the purpose of improving the accuracy and resilience of predictions, the system that has been presented incorporates a number of different deep learning models. These models include Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN). The ensemble technique is an efficient method for addressing the inherent complexity that are present in air quality data. This is accomplished by using the strengths of many models. By allowing proactive control of air quality and informed policy-making, the installation of such a system has the potential to make a substantial contribution to the sustainability and liability of urban settings. The integration of other data sources, such as data on traffic and industrial activities, and the investigation of sophisticated ensemble methods are two potential future paths for study. Both of these approaches are intended to further enhance prediction performance.

**Keywords:** Air Pollution, Convolutional Neural Networks (CNN), Smart Environmental Factors, Ensemble Learning, Deep Learning, Pollution Prevention, Sustainability.

**How to Cite:** Homa Rizvi; Sunny Kumar; Dr. Yusuf Perwej; Farheen Siddiqui; Dr. Nikhat Akhtar (2025) A Data-Driven Ensemble Deep Learning Approach to Urban Air Quality Prediction and Management. *International Journal of Innovative Science and Research Technology*, 10(12), 1382-1391. https://doi.org/10.38124/ijisrt/25dec1067

## I. INTRODUCTION

Smart city sustainability is a concept that focuses on using technology and data to create a city that is functional, liveable, and good for the environment [1]. One of the most important parts of making a smart city sustainable is controlling and lowering air pollution [2]. Air pollution is bad

for people's health, the environment, and the quality of life in cities [3]. So, being able to accurately estimate air pollution levels is a big part of solving [4] this problem well [5]. In recent years, improvements in the availability of data and forecasting techniques have made air quality forecasts a more important part of studies on air pollution. There are three main types of models: statistical, machine learning [7], and

hybrid [8]. In many places, air quality is a big worry. It becomes a crucial matter to mitigate or avert the repercussions of air pollution [9]. You may start taking steps to protect yourself once you know the air quality. But looking at the data and coming up with sensible answers is a really hard job [10]. So, it is important to use effective methods and strategies to find information that is buried in data, analyse huge data more quickly and effectively, and make the unseen apparent [11]. A prospective system for forecasting and overseeing air pollution in advance is very important for governmental policy-making and public health. Because the data is up-to-date, time forecasts are very important themes that researchers and academics need to pay close attention to [12]. To address these constraints, deep learning algorithms have been progressively used for air pollution forecasting. Deep learning models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have shown enhanced efficacy in collecting spatial and temporal patterns in data, respectively. But using just one form of model could not take full use of the many parts of air quality data, which might lead to forecasts that aren't as good as they could be [15]. Ensemble learning, which integrates many models to make predictions more accurate and reliable, is a possible approach [16]. An ensemble technique may provide air quality forecasts that are completer and more accurate by combining several deep learning models, each of which is good at finding distinct data patterns [17]. This research presents an ensemble deep learning-based air pollution prediction system designed for sustainable smart cities. The proposed system's goal is to provide accurate, realtime forecasts that will help policymakers and other decisionmakers act quickly to reduce the effects of air pollution. This paper is organized like this: The second part looks at similar works and systems that are already in place, pointing out their pros and cons [18]. After then, the suggested system is explained in full, including its structure, processes for putting it into action, and ways to measure its success. Then, the outcomes of the suggested system are shown and spoken about. The study ends with a summary of the results and suggestions for further research [19].

## II. BACKGROUND

Recent research has redirected its emphasis to sophisticated statistical learning algorithms for evaluating air quality and forecasting air pollution. [20] and [21] used neural networks to create models that predict the concentrations of certain pollutants, including particulate matter with a diameter of less than 10 microns (PM10). The research in [22] introduced a random forest-based model, RAQ, for the classification of Air Quality Index (AQI) values. After that, they used deep neural networks to classify AQI [23]. In [22], artificial neural network (ANN) models [24] were used to forecast PM10 concentrations inside a subway station, integrating factors such as train frequency, outside PM10 levels, and ventilation system data [25]. When compared to experimental data, the ANN models showed significant predictive power, with correlation values between 0.18 and 0.63. The model [27] got an accuracy rate of 67% to 80%, depending on how the subway platform was built and how deep it was. Li et al. [28] proposed an AC-LSTM

approach related to deep learning that uses a 1D-CNN, an attention-based network, and an LSTM network to estimate the concentration of PM2.5 in cities. The author included PM2.5 concentrations and meteorological data from proximate air quality monitoring stations as inputs to the given approach, rather than using air pollutant concentrations. In [29], a system was developed to provide real-time reporting of air quality status via a cloud server, which sends alerts about the presence of dangerous pollution levels in the air. The AAA-oriented ENN technique predicts the air quality in the future and is used to figure out what kind of air pollution is there. Zhang et al. [30] proposed a deep learning (DL) approach using a Bi-LSTM and Autoencoder (AE) to predict PM2.5 concentrations, revealing many climatic factors and their correlations with PM2.5. The approach encompasses many components, including Bi-LSTM, data pre-processing, and the AE layer.

Ma et al. [31] introduced an innovative methodology that combines a deep learning network, the inverse distance weighting (IDW) algorithm, and the BLSTM network for spatiotemporal predictions of air pollution across various temporal resolutions. Du et al. [32] presented a deep learning methodology, iDeepAir, to predict surface-level PM2.5 concentrations in the Shanghai megacity and correlate it with the MEIC emission inventory to analyze the impact of urban transportation on air quality. To enhance the method's importance, [33] Layer-wise Relevance Propagation (LRP) was used. Li et al. [33] developed a hybrid CNN-LSTM methodology by integrating the CNN with the LSTM-NN [34] to forecast the subsequent 24-hour PM2.5 concentration [35]. Four models were developed: the univariate CNN-LSTM technique, the univariate LSTM method [36], the multivariate CNN-LSTM method [37], and the multivariate LSTM approach [38]. Recent studies [39] used residuals from SARIMA models as inputs to deep learning architectures for PM2.5 forecasts in Beijing. They discovered that this hybrid model surpassed both independent SARIMA and deep learning models. Ma et al. (2019) [40] expanded this methodology by combining BiLSTM networks with SARIMA residuals, resulting in enhanced precision in air quality forecasts at increased temporal resolutions. Combining SARIMA with neural networks has shown to function better for predicting air pollution. Alhirmizy and Qader (2019) [41] used Long Short-Term Memory (LSTM) networks for multivariate time-series forecasting in Madrid, Spain, with good accuracy for pollutants such as NO2 and CO. Similarly, Pagano and Barbierato (2024) [42] applied similar methodology in Brescia [43], Italy. Ansari and Alam (2024) integrated SARIMA with LSTM [44] and refined the models by Bayesian [45] optimization, yielding superior outcomes compared to independent models [46]. A deep learning algorithm was used to predict PM2.5 levels in Beijing for a brief period of time [47]. Liu et al. [48] used a wind-sensitive attention mechanism in a long short-term memory (LSTM) neural network to improve PM2.5 predictions by integrating wind pattern data. Also, [49] built a complete air quality early warning system that includes parts for estimating, predicting, and evaluating air pollution.

## III. EXISTING SYSTEMS

The Environmental Protection Agency (EPA) makes systems that employ standard models to provide a rough idea of air quality, but they aren't accurate enough for precise forecast or real-time usage. AirVisual and other systems use machine learning techniques to predict how polluted the air will be [50]. These systems are more accurate than older ones, but they may not be able to fully use the power of deep learning models. DeepAir is an example of a project that combines RNNs with CNNs [51] to make predictions more accurate. These systems show promise, but they typically run into problems with the amount of computing power they need and how they handle data [52].

## > UCI Dataset

It is very necessary to make use of real data when it comes to the development of machine learning models. The dataset that was made available to us by the UC Irvine Machine Learning Repository was used in the course of our scholarly investigation. It is common known that this is a trustworthy source of information and data for the research [53]. It not only includes readings from sensors that are updated in real time, but it also includes extra information on major chemicals that were gathered from an air pollution monitoring station that is situated in a town found in Italy. The collection that we have is made up of 9471 entries and 15 characteristics that are distinctive to the collection. On the other hand, there are a few of its characteristics that are lacking values, and they were fixed during the pre-processing step, which is seen in figure 1.



NB(NISHANT\_BHADAURIA) · UPDATED 9 YEARS AGO

## **UCI ML Air Quality Dataset**

Discussion (1)

https://archive.ics.uci.edu/ml/datasets/Air+Quality



Code (11)

## About Dataset

Data Set Information:

Data Card

The dataset contains 9358 instances of hourly averaged responses from an array of 5 metal oxide chemical sensors embedded in an Air Quality Chemical Multisensor Device.

The device was located on the field in a significantly polluted area, at road level, within an Italian city.

Usability ① 7.06

License

Unknown

Expected update frequency Not specified

Fig 1 The UCI Air Quality Dataset

Suggestions (0)

## IV. METHODOLOGY

The suggested ensemble deep learning method for predicting air pollution combines many deep learning models to make predictions more accurate and reliable. The architecture has three main parts: collecting data, training the model, and making predictions. Get real-time air quality data from several sensors all throughout the city [54]. The information contains the amounts of pollutants like PM2.5, PM10, NO2, SO2, and CO, as well as weather data like temperature, humidity, and wind speed. Use historical air quality data to train many deep learning models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. As shown in figure 2, each model captures distinct parts of the data. For example, LSTM collects temporal patterns while CNN catches spatial information [55]. Use ensemble methods like weighted averaging and stacking to combine the predictions of several models. This method makes sure that the final forecast uses the best parts of each model, which makes it more accurate and reliable. Before the models are trained, the data that was

gathered is cleaned up to make sure it is consistent and get rid of any strange values [56]. This includes things like normalizing, dealing with missing values, and aligning data from multiple sensors in time. LSTM networks are great for simulating how time-series data changes over time. The LSTM model learns from sequences of past air quality data [57]. At time t, let Xt be the input vector that comprises meteorological data and pollution concentrations. The LSTM network uses this input to guess what the air quality will be like at the following time step, Xt+1. You may use the following equations to update the hidden state ht and the cell state Ct:

 $f_{t} = \sigma(Wf \cdot [ht-1,Xt] + bf)$   $it = \sigma(Wi \cdot [ht-1,Xt] + bi)$   $C_{t}^{\sim} = \tanh(WC \cdot [ht-1,Xt] + b_{C})$   $Ct = ft * C_{t-1} + it * C_{t}^{\sim}$   $ot = \sigma(Wo \cdot [ht-1,Xt] + bo)$   $ht = ot * \tanh(Ct)$ 

Where

 $\sigma$  is the sigmoid function,

\* denotes element-wise multiplication, and

Wf, Wi, WC, Wo and

bf,bi,bC,bo are the weights and biases of the respective gates.

The CNNs are good at picking up spatial information from the data they get [58]. The CNN model looks at the geographical data to find patterns and connections that impact air quality. Let *X* be the matrix of air quality data that you put in. The CNN uses convolutional filters to get features out of the data.

$$F_{i,j} = \sigma(\sum_{k,l} Xi + k, j + l \cdot Wk, l) + b$$

Where

Fi,j is the feature map,

W is the filter,

b is the bias, and

 $\sigma$  is the activation function.

For the purpose of enhancing overall performance, the predictions of the separate models are aggregated via the use of ensemble methods. The use of weighted averaging, in which the forecast of each model is allocated a weight depending on its performance, is one strategy that is quite successful.

$$Y^{=\sum_{i=1}^{n} wiY_i}$$

Where

Y<sup>^</sup> is the final prediction,

Y<sup>i</sup> is the prediction from the i-th model,

wi is the weight assigned to the i-th model, and

n is the number of models.

Stacking is a further method, which involves the training of a meta-model to integrate the predictions of the basis models.

$$Y^{\wedge} = g(Y^{\wedge}1, Y^{\wedge}2, ..., Y^{\wedge}n)$$

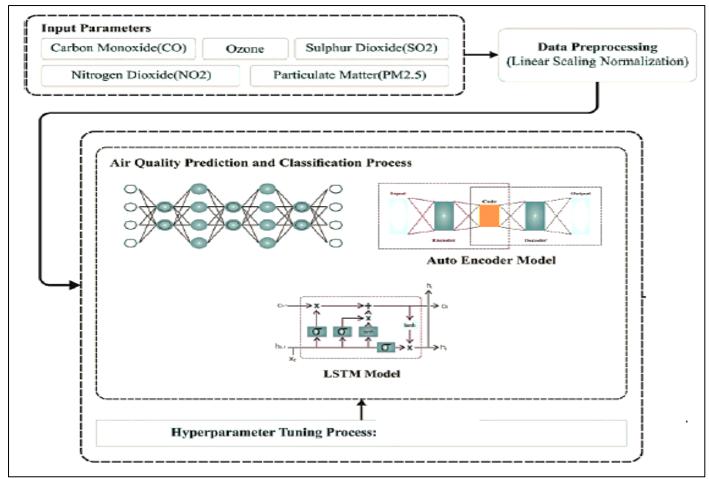


Fig 2 The Proposed System

https://doi.org/10.38124/ijisrt/25dec1067

## V. OUTCOME

Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared are some of the metrics that are used in order to assess the effectiveness of the ensemble model.

$$\begin{aligned} \text{MAE} &= \sum_{i=1}^{n} \mid \text{Yi} - \text{Y}^{i} \mid \\ \text{RMSE} &= \sqrt{\frac{1}{n}} \sum_{i=1}^{n} (\text{Yi} - \text{Y}^{i}) \ 2 \\ \text{R}^{2} &= 1 - \frac{\sum_{i=1}^{n} (\text{Yi} - \text{Y}^{i}) 2}{\sum_{i=1}^{n} (\text{Yi} - \text{Y}^{i}) 2} \end{aligned}$$

Where

Yi s the actual value,  $Y^{i}$ 

Is the predicted value,

Y is the mean of the actual values, and

n is the number of observations.

The accuracy and robustness of the model are extensively evaluated using these criteria, which yield a complete score. In order to evaluate the effectiveness of the proposed ensemble deep learning model for air pollution prediction, we compare it to a number of baseline models [59]. These baseline models include conventional statistical methods, individual deep learning models (LSTM and CNN), and machine learning models (Random Forest and Gradient Boosting). Metrics such as Mean Absolute Error (MAE), Root Mean [60] Squared Error (RMSE), and R-squared (R2) are used in order to evaluate the models. Please refer to table 1 below for a presentation of the findings. The dataset that was utilized for the study included data on air quality as well as meteorological information that was gathered from a significant metropolitan region over the course of one year [61]. In addition to hourly observations of meteorological

parameters (temperature, humidity, wind speed), the data now contains hourly measurements of pollutants (PM2.5, PM10, NO2, SO2, and CO). The dataset is broken up into three sets: the training set (80 percent), the validation set (10 percent), and the test set (10 percent).

According to the findings, the ensemble deep learning model that was suggested performs better than any other model overall, considering all of the assessment measures. As compared to the baseline models, the ensemble model gets the lowest mean absolute error (MAE) of 6.97, which indicates that it is more accurate in forecasting the levels of air pollution overall [62]. The historical ARIMA model has the largest MAE, which demonstrates the limits of this model when it comes to dealing with complicated and nonlinear data on air quality [63]. A further confirmation of the ensemble model's greater prediction accuracy is the fact that it has the lowest RMSE, which comes in at 10.55. When the RMSE values are lower, it indicates that the predictions are more [64] accurate and have less significant mistakes than when the values are higher. With an R2 score of 0.96, the ensemble model achieves the maximum possible value, which indicates that it accounts for 93% of the variation in the data pertaining to air pollution. Additionally, this model beats more complex machine learning [65] models such as Random Forest and Gradient Boosting, which is a substantial improvement over the classic ARIMA model, which has a coefficient of determination of 0.76. The performance of LSTM and CNN models is [66] superior to that of classical and machine learning methods, with LSTM models yielding somewhat better results than CNN models. An additional improvement is shown by the hybrid model that combines LSTM with CNN. This model takes use of [67] both the temporal and spatial characteristics of the data. It has been shown that the ensemble model, which incorporates predictions from a number of different deep learning models, has the best performance [68]. This exemplifies the benefits of ensemble learning, which include the ability to capture a wide variety of data patterns and enhance the liableness of predictions.

Table 1 Performance Metrics of Machine Learning Models

Model	Performance Summary for 80% - 20%		
	MAE	RMSE	$\mathbb{R}^2$
Gradient Boosting	9.88	13.99	0.89
CNN	8.92	12.88	0.91
Random Forest	10.44	14.66	0.87
LSTM	8.55	12.33	0.92
Ensemble Model	6.97	10.55	0.96
ARIMA	13.55	18.72	0.76

An ensemble deep learning-based air pollution prediction system for sustainable smart cities has been suggested, and the comparison analysis demonstrates that this system is successful. The ensemble technique addresses the difficulties of air quality data [69] by integrating many deep learning models, which results in a considerable improvement in prediction accuracy and resilience. The improved performance of the system across a variety of

assessment measures reveals its ability to give accurate, realtime forecasts of air quality [70]. This has the potential to provide timely interventions and informed policy choices that are aimed at mitigating the consequences of air pollution. In further study, it may be possible to investigate the possibility of combining new data sources and sophisticated ensemble methods in order to further improve the performance of the system, as seen in figure 3.

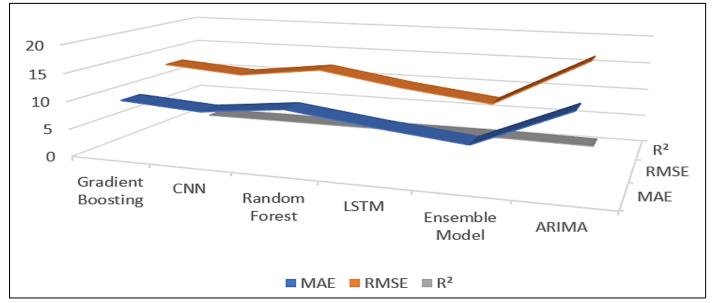


Fig 3 Analysis Report

## VI. CONCLUSION

Because air pollution is a significant environmental and health problem on a worldwide scale, it is necessary to provide accurate and timely forecasts of pollutant levels in order to reduce the negative impacts of this pollution. Recent developments in machine learning and deep learning have made it possible to make accurate predictions about air quality: nevertheless, it is still difficult to implement these models in environments where resources are limited for realworld applications. The purpose of this study is to provide an ensemble deep learning-based system for predicting air pollution that is specifically designed for metropolitan areas. The system that has been developed displays greater accuracy and resilience in the management of the complexity of air quality data. This is accomplished via the integration of numerous deep learning models. A dependable instrument for predicting real-time air quality, the ensemble model outperforms conventional statistical approaches, individual machine learning models, and standalone deep learning models, according to the comparison study. This demonstrates that the ensemble model is superior to more traditional statistical methods. The findings of this research shed light on the potential of ensemble deep learning algorithms in the field of environmental management and monitoring. There is a possibility that future study may concentrate on increasing the data sources that are included into the prediction models. For example, traffic patterns, data on industrial activities, and information from social media might be incorporated in order to capture a wider variety of

elements that influence air quality. In addition, the investigation of more sophisticated ensemble methods, such as adaptive boosting or deep stacking, has the potential to substantially improve prediction performance. Ultimately, the ensemble deep learning-based air pollution prediction system that has been developed provides a potential solution for sustainable smart cities. It lays the groundwork for proactive air quality management and contributes to the creation of urban settings that are both healthier and more sustainable.

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