Air Contamination Prediction and Comparison Using Machine Learning Algorithms

P. ArunaKumari, Y. Vijayalata, G. Susmitha Valli, and Y. Lakshmi Prasanna

Abstract Dealing with air contamination presents a significant environmental hazard in the urban environment. Constant monitoring of contamination data empowers local authorities to analyse the current traffic circumstance of the city and settle on choices likewise. Arrangement of the Internet of Things-based sensors has extensively changed the elements of foreseeing air quality. Existing exploration has utilized distinctive artificial intelligence learning tools for contamination prediction; however, near examination of these procedures is needed to have a superior comprehension of their handling time for numerous datasets. This paper tends to the test of foreseeing the air quality index (AQI), with the aim to predict the contamination on different studies, utilizing two machine learning algorithms: neural networks and support vector machines. The air contamination datasets downloaded from the Central Pollution Control Board (CPCB). The proposed machine learning (ML) model is used to predict the Delhi Air Quality Index (AQI) data and compare it with the actual and predicted data.

Keywords Machine learning · Neural networks · Support vector machines

1 Introduction

Air is the most fundamental characteristic asset for the presence and endurance of the whole species of earth. All types of species which include plants, insects, and creatures rely upon the air as it is their fundamental endurance. Hence, all organic

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entities need the fresh air which is liberated from unsafe gases to live their life. In 2008, the Blacksmith institute did research on air pollution and noticed the most contaminated spots, the two of the most noticeably terrible contamination issues on the planet are metropolitan air contamination and indoor air contamination [1]. The major causes of air contamination are industrial wastes, automobiles, agricultural activities, exhausts from factories, mining, etc., which causes long haul and transient wellbeing impacts. It is tracked down that the old and little youngsters are more affected by air contamination. Short period side effects are burning eyes, loose nose, itching in the throat, headaches, skin allergies, respiratory problems, and pneumonia. Few long-term side effects are cancer in the lungs, brain misfunctioning, damage to the liver, kidney, coronary illness, and respiratory infections such as emphysema [2]. Also, it affects the whole ecosystem like the formation of smog with solid and liquid particles which is a visible type of air pollution that also sometimes having different shapes and variant colours. Likewise adds to the ozone layer damage, which shields the planet from direct UV beams from the sun. Few more adverse consequences of air contamination particles fall on earth eventually which directly pollutes the water surface bodies and soil. Those particles can affect agriculture causes less yield. The particles of nitrogen oxide and sulphur dioxide in the air can cause acid rain formations while mixing with water in the upper atmosphere, which damages the planet's surface soil, wildlife, rivers, lakes, and trees. Thus, air contamination is quite possibly the most disturbing worry for us today. Tending to this worry, in the past years, numerous analysts have invested loads of time in considering and creating various models and strategies in air quality examination and assessment.

Air quality prediction took place by following traditional methodologies from all these years. These methodologies include a collection of raw manual data and evaluation. There are several conventional methodologies or strategies available for air quality forecast by using numerical and factual procedures [2]. In these strategies, at first an actual model is planned and information is coded with numerical conditions. Besides such strategies may also experience the ill effects due to the drawbacks like:

1. Less accuracy while prediction—they are unable to predict maximum and minimum levels of pollution
2. Inappropriate methodologies for output prediction
3. Implementation of complex algorithms
4. Amalgamation of old and new data.

In spite with the headway in innovation and exploration, options and in contrast to conventional strategies, several new strategies or methodologies are proposed which makes use of AI and big data approaches. Even though numerous scientists have created and utilized analytical models of big data and AI-based models to direct air quality assessment to accomplish better precision in assessment and prediction. This paper is mainly focused on few scientific researches and study on the available methodologies published on air pollution prediction. The significant target is to give a depiction of the tremendous exploration work and valuable audit on the present status of the workflow on AI, ML, deep learning, and big data approaches for air quality assessment and prediction (Table 1).

Table 1 Health statements for AQI categories (this table was adapted from the Central Pollution Control Board's National Air Quality Index Report)

AQI	Associated health impacts
Good (0–50)	Minimal impact
Satisfactory (51–100)	May cause minor breathing discomfort to sensitive people
Moderately polluted (101–200)	May cause breathing discomfort to the people with lung disease such as asthma and discomfort to people with heart disease, children and older adults
Poor (201–300)	May cause breathing discomfort to people on prolonged exposure and discomfort to people with heart disease
Very poor (301–400)	May cause respiratory illness to the people on prolonged exposure. Effect may be more pronounced in people with lung and heart disease
Severe (401–500)	May cause respiratory effects even on healthy people and serious health impacts on people with lung/heart diseases. The health impacts may be experienced even during light physical activity

The paper is structured as per the following. Section 2 shows the striking work done by the researchers to estimate air quality. Section 3 presents data and perceptions identified with the information and strategies utilized in this investigation. Section 4 talks about the investigations and results of this examination. At the end, future extension of the work is being discussed in the fifth segment.

2 Related Work

A deep learning algorithm uses various layers to automatically extract high-level features from raw data in a dynamic manner. Deep learning designs such as RNNs are used to model sequential data. This function contains cyclical connections wherein the preceding time steps taken into account as inputs to the present time. Several RNNs use a backpropagation and propagation through time (BPTT) procedure to propagate errors and update weights. In any event, gradients can disappear and explode while preparing an RNN. The slope yield in the neural network (NN) model causes massive estimations of the gradients, if more than one with numerous layers. It is due to this phenomenon that the trainable weights have significant differences in their quality with each cycle, which, in turn, increases the effect of the layer beneath the trainable weight. However, when they are less than 1, the gradients' effects on the underlying layers are negligible. To deal with these issues, LSTM has been presented as a way to reduce their impact.

The LSTM is a particular RNN type that is intended to achieve a higher level of accuracy than regular RNNs when modelling temporal sequences. During recurrent shrouded layers, the memory blocks contain extraordinary units. In the memory blocks, self-replicating memory cells store the temporal state of the organization as well as unique multiplying elements called entryways that control the progress of data.

In 2004, the Department of Electronics addresses the prediction problems of Ozone and PM10 toxins [3]. Researchers proposed a statistical approach using feed-forward neural networks (FFNN) which is compared with pruned neural networks and lazy learning. The PNN is a constitute of parameter parsimonious approach which mainly depends on dumping the redundant parameters of FCNN. The lazy learning is an approach of local linear algorithm which performs the prediction using local learning procedure. Using these three algorithms, the authors trained and tested to predict the O3 and PM10 levels, but the prediction accuracies are does not make any difference [3].

In the year 2008, researchers from the Shandong University proposed an approach to find the quality of air using back propagation neural networks (BPNN) on rough set theory [4]. In this experiment, first they minimized the data monitoring of the contamination sources utilizing the hypothesis of the harsh set, from the clean guidelines. At that point, the topological design of the multi-facet BPNN and the nerve cells of the suggestive layer is characterized by these principles. From that point forward, the associated weight benefits of comparing hubs of the BPNN are found out. Utilizing BP math, the forecast model is prepared with the checking data of the contamination sources and air screen stations for acquiring its different boundaries.

In the year 2009, Prediction of Indoor Air Quality Using Artificial Neural Networks was published by the University of Science and Technology of Beijing. In this research work, they proposed an ANN-based prediction model to predict the air quality. They fed three toxic indoor air contamination gases out of six as input to the network, and an occupant symptom metric is used to measure the air quality and given as an output variable [5].

In the year 2010, from the State Environmental Protection Key Laboratory with the collaboration with Nankai University proposed a GA-ANN model to predict air quality. This model is an advanced ANN model called genetic algorithm and artificial neural networks. They have used genetic algorithm to select the factors from the dataset which is directly fed to ANN model for training and testing. In order to experiment, they have used Tianjin city air pollution data. Finally, they compared the GA-ANN with ANN and PCAANN models [6].

In the year 2015, C. Xiaojun et al. proposed an IOT-Based air pollution monitoring and detection system [7]. They used a huge volume of sensors to make sure the accuracy of monitoring also which reduces monitoring cost also makes the data systematic and accessed using IOT and telematics. The data received from the sensors need to be processed to find out the predicted value in order to do that they have used ANN model and Bayesian regularization model for analysing the data [7].

In the year 2017, Gazi University published a paper on air quality prediction using deep learning model [8]. The authors used RNN—recurrent neural network model-based long short memory (LSTM) networks model to predict future air quality index values in metropolitan cities.

In the year 2018, proposed a deep learning-based spatial temporal approaches to detect the air quality [9]. The authors tried to predict the quality of air for 48 h using different NN—neural networks as follows: (1) ANN, (2) CNN, and (3) LSTM model to extract spatial temporal relations [9].

In 2020, Daniel Schürholz et al. proposed an artificial intelligence-based approach to find out the air quality prediction [10]. The authors in their research experimented a novel setting expectation model that incorporates setting to computer concepts to consolidate an exact air contamination forecast calculation utilizing long short-term memory and deep neural networks with data.

3 Methodology and Dataset

3.1 Data Acquisition

Out of Delhi's 1484 square kilometres, 783 are devoted to the rural areas and 700 to the urban areas. There are currently 19 million people living in Delhi. By 2028, Delhi will be the most crowded city in the world, according to the World Urbanization Prospects of the United Nations 4. Although there have been numerous steps none of the measures taken to control air pollution have been particularly beneficial. The authors choose to explore Dwarka as a possible location for our investigation. In addition to being a sub-city in Delhi, it is not far from Gurugram, the world's most polluted city. A contamination hotspot in Delhi is Dwarka. A total of 170 stations (areas) (expresses) gathered from 18 states and 102 urban areas with a total of 102 urban communities were used to obtain pollution concentration and meteorological data. The data collected for the NSUT (formerly NSIT) station in Dwarka's Sector-3 has been analysed. When comparing NSUT data with data from different stations, there were a few little holes (non-designated values) that would equal a couple days up to half a month in a year. The authors chose 3.5 years as the period of data. The data is chronologically dated from 1 April 2015 to 31 March 2017, and from 1 October 2017 to 1 April 2019 and are unable to access data from April 1, 2017 to September 30, 2017 [11]. A breakdown of the air pollutants and meteorological boundaries that were used in this analysis can be found in Tables 2 and 3.

In order to conduct this study, air pollution data was collected from numerous monitoring stations. In Fig. 1, Anand Vihar can be seen. Secondly, polluted regions are where these observation stations are located. Furthermore, the choice of these stations demonstrated the complexity and heterogeneity of predicting city-level contamination patterns. For example, the pollution concentrations for NO_2, CO, O_3, SO_2, PM_{10}, and $PM_{2.5}$ were collected from the Central Pollution Control Board (CPCB) site and a "Noise and Air Contamination Observing Framework" to gather pollution levels. A Wi-Fi module transmits data to the cloud, and a SD card stores data on the device itself, and multiple noise and gas sensors work together as part of this framework. At the initial IoT stage, the data is saved on the cloud where it can

Table 2 List of pollutants considered

S. No.	Parameters	Unit
1	CO (carbon monoxide)	mg/m^3
2	NO (nitrogen oxide)	$\mu g/m^3$
3	NO_2 (nitrogen dioxide)	$\mu g/m^3$
4	Ozone	$\mu g/m^3$
5	$PM_{2.5}$ (particular matter 2.5 mm)	$\mu g/m^3$
6	SO_2 (sulphur dioxide)	$\mu g/m^3$

Table 3 Meteorological parameters

S. No.	Parameters	Unit
1	Temperature	°C
2	RH (relative humidity)	%
3	SR (solar radiation)	W/mt^2
4	WS (wind speed)	m/s

be accessed by anyone. Likewise, authors extracted data from the above-referenced sources for affecting elements such as wind speed, wind heading, temperature, and relative humidity.

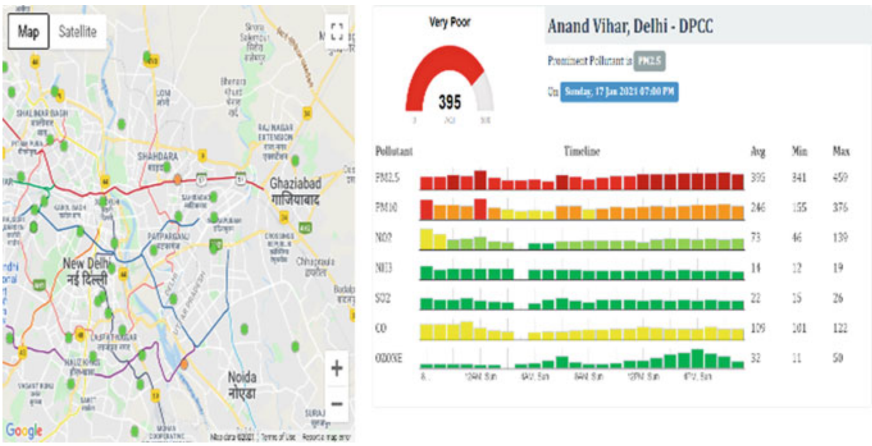

Fig. 1 National air quality index pollution monitoring centres

	City	Datetime	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	AQI_Bucket
15	Delhi	01-01-2015 16:00	211.51	340.66	13.09	37.08	47.07	33.54	15.24	12.33	34.35	3.51	5.85	4.73	456.0	Severe
16	Delhi	01-01-2015 17:00	191.12	257.40	15.44	38.40	51.24	34.98	13.11	18.00	34.38	3.58	5.23	3.78	450.0	Severe
17	Delhi	01-01-2015 18:00	218.44	351.01	22.85	44.73	59.26	34.80	18.35	19.17	38.42	3.67	5.93	4.98	446.0	Severe
18	Delhi	01-01-2015 19:00	296.80	600.95	69.20	47.76	101.68	34.25	16.67	21.50	49.12	14.75	27.13	8.78	475.0	Severe
19	Delhi	01-01-2015 20:00	336.43	714.63	148.42	46.31	171.10	35.75	12.17	17.67	56.44	26.56	45.62	9.99	480.0	Severe

Fig. 2 Refined data

3.2 Data Pre-processing

3.2.1 Data Refinement

After cleaning the input data by removing any missing values, the analysed data was examined. An imputer function is used to perform the interpolation to determine whether a missing value (NaN) occurs if there arises an occurrence of the target object, i.e., the polluted gas. Here, mean values are utilized as a method of assessment (Fig. 2).

3.2.2 Data Visualization

Different pollutants can be pictured utilizing a chart that gives experiences about the ascent and fall of their concentration in air. The histogram graph for every one of the pollutants is plotted with *x*-axis speaking to the number of tests and *y*-axis speaking to concentration in $\mu g/m^3$ (Figs. 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12).

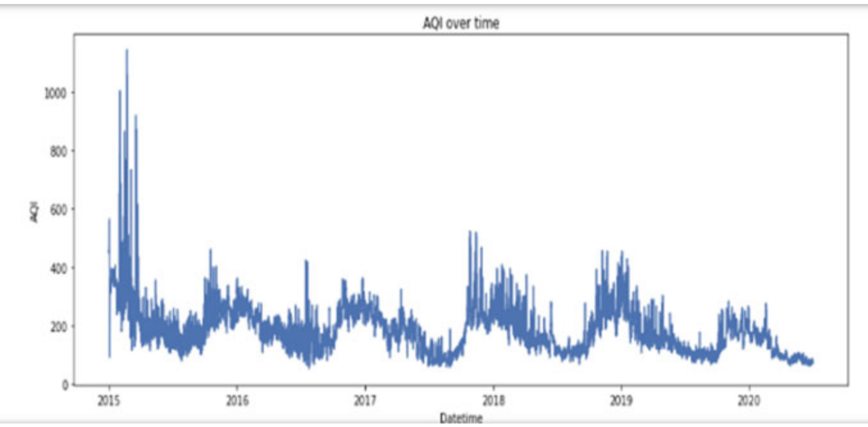

Fig. 3 AQI over time period

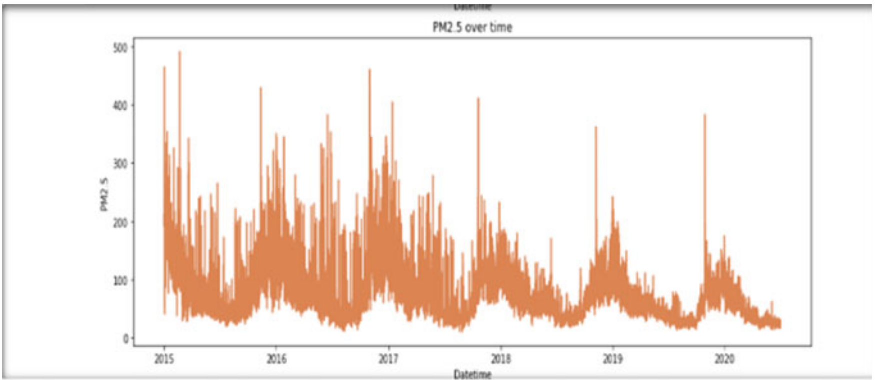

Fig. 4 $PM_{2.5}$ over time period

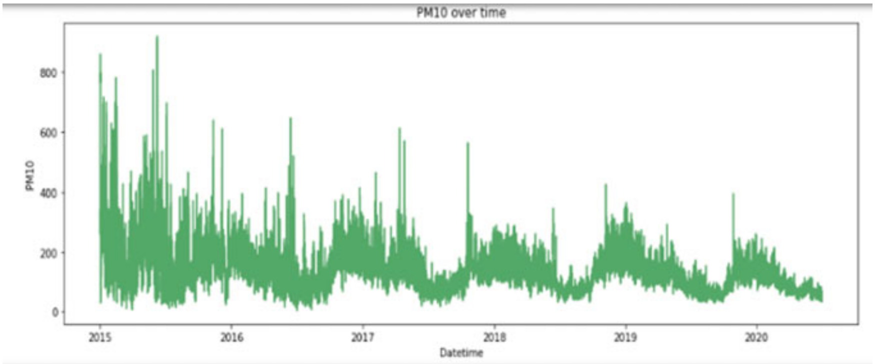

Fig. 5 PM_{10} over time period

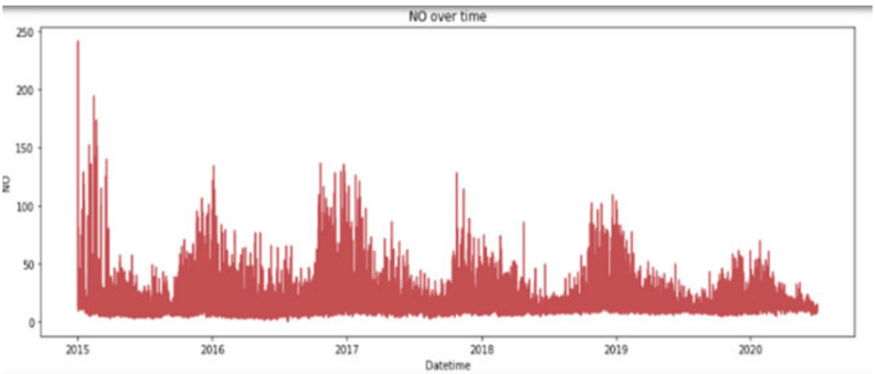

Fig. 6 Nitrous oxide (NO) over time period

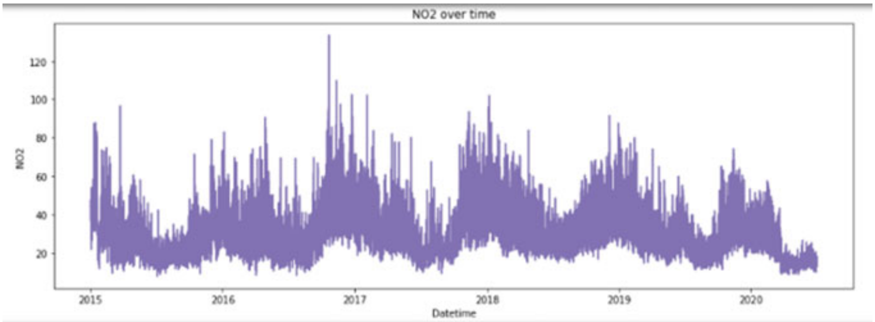

Fig. 7 NO_2 over time period

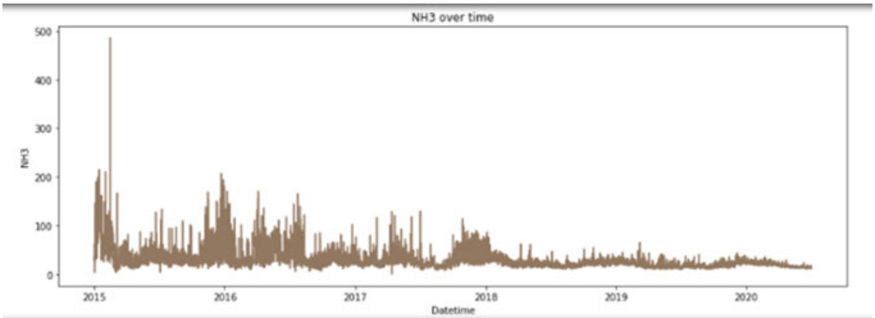

Fig. 8 NH_3 over time period

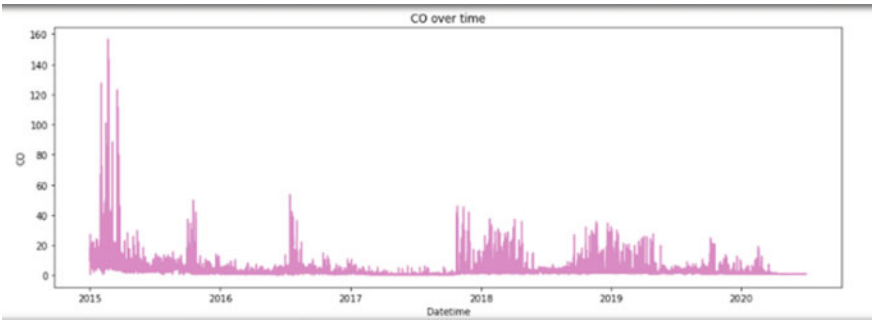

Fig. 9 CO over time period

3.2.3 Splitting Data

In order to evaluate the exhibition of a model, it is important to appropriately fit training, validation, and test data. Data does not have any standard way of being separated into preparations, validations, and tests. A half year's data has been selected

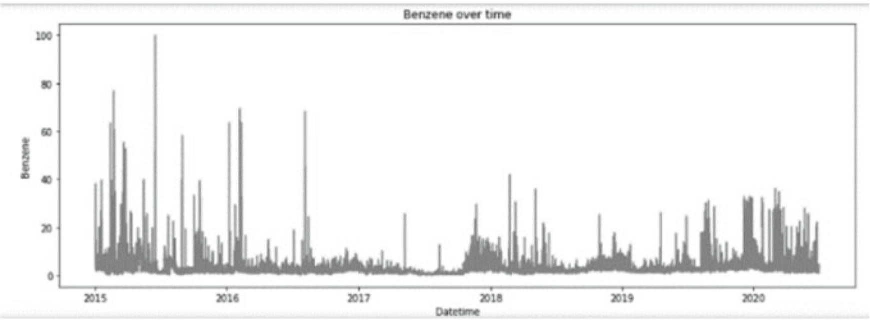

Fig. 10 Benzene over time period

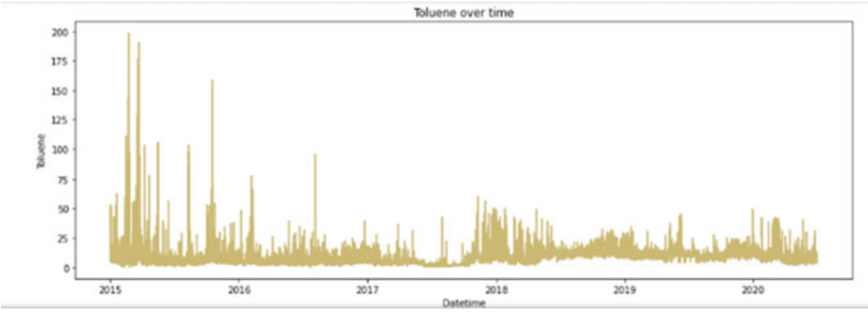

Fig. 11 Toluene over time period

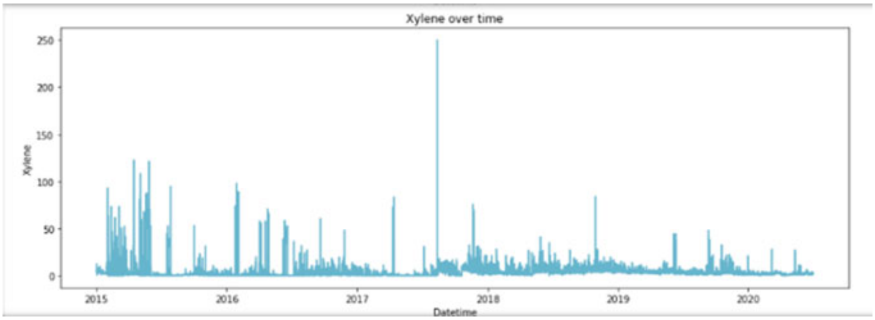

Fig. 12 Xylene over time period

for approval, a year's data has been chosen for testing, and 2 years' worth of data has been chosen for preparing. The training component contains a time-series dataset validation that includes a dataset from 1 April 2015 to 31 Walk 2017, validation includes a dataset from 1 October 2017 to 31 Walk 2018, and testing includes a dataset from 1 April 2018 to 1 July 2020. Each data entry represents a time series data point and refers to pollutants and metrological boundaries.

Figure 2 reveals that the features in the study of the information belong to various reaches, means, and standard deviations. As a result of non-comparability of quality scopes among factors, gradients may slack and fade before meeting nearby/global minima. The Min–Max normalization allows different features to take on qualities in similar reach, eliminating the model learning issue. This allows gradients to merge more rapidly as gradients are standardized within a range of 0–1.

3.3 LSTM Model

3.3.1 Architecture

An LSTM graph is depicted in Fig. 3 as a part of the neural network architecture. There are four layers in the model: input layer, two LSTM layers, and dense layer. The LSTM layer relies on the input layer to create sequential data. The number of time steps determines how many sequences Seqi have. There are k feature vectors for each sequence. On the diagram, X represents a vector, where each of the features is represented by X_t. X_t represents the present time's concentration of pollutant p, thus Ctp. It also contains weather parameters such as temp, rh, sin, and s.r. In turn, the LSTM layer is fed with these sequences. There are several memory blocks in each LSTM layer. Gates are special multiplicative units that serve as multiplicative links between memory cells. An information gate controls the flow of information in a network which is stored in a memory cell. An LSTM cell is made up of three types of gates—output gate, input gate, and forget gate. An input gate is responsible for the flow of inputs into the memory cell, while an output gate is responsible for distributing outputs from the memory cell to the rest of the network. Forget gates address a weakness of LSTM models by allowing them to enter continuous input streams without segmenting them into sub sequences. Adaptively forgetting or resetting the memory of the cell the scaled internal state is added as input to the cell via the cell's recurrent connection. As shown in Fig. 13, an LSTM cell can be simplified to represent a box.

3.3.2 Sequential to Supervised Conversion

It is necessary to feed LSTMs marked input and yield data since it is a supervised learning algorithm. This allows sequential data to be transformed into supervised data prior to fitting the LSTM model.

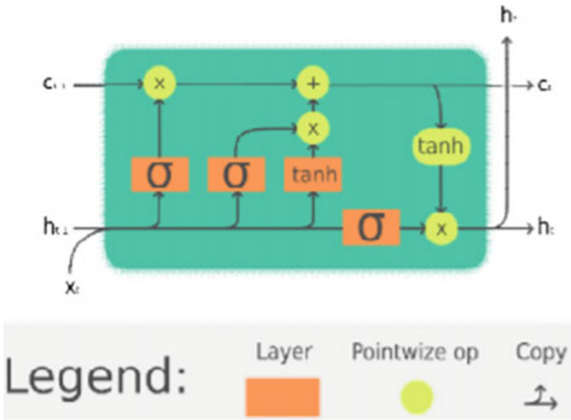

Fig. 13 LSTM cell

3.4 Model Fitting

Datasets must be prepared and tested before being used. Earlier in the model, which will determine network boundaries the preprocessed data satisfied to the model. To gauge the performance of a neural network, an optimizer is required. In neural networks, optimizers are methods or calculations used for setting various parameters such as weights, bias, and learning rates. There are different optimizers, and the decision is based on which one of them addresses the issue at hand. It is important to use different learning rates for different pollutants when predicting $PM_{2.5}$ concentration in the air (Fig. 14).

3.5 Model Evaluation Parameters

It is calculated for the model, the mean square error (RMSE), to measure how accurate the predictions are. An error of approximately 1% was produced by the proposed model.

3.5.1 Root Mean Square Error

To assess the model's performance, we calculated three error functions: the root mean square error (RMSE), the mean absolute error (MAE), and the efficiency coefficient (R^2). They can be expressed mathematically as root mean square errors (RMSEs).

$$\mathrm{RMSE} = \left\{ \frac{1}{n} \sum_{i=1}^{n} \left(y_{i_{\mathrm{pred}}} - y_{i_{\mathrm{true}}} \right)^2 \right\}^{\frac{1}{2}} \quad (1)$$

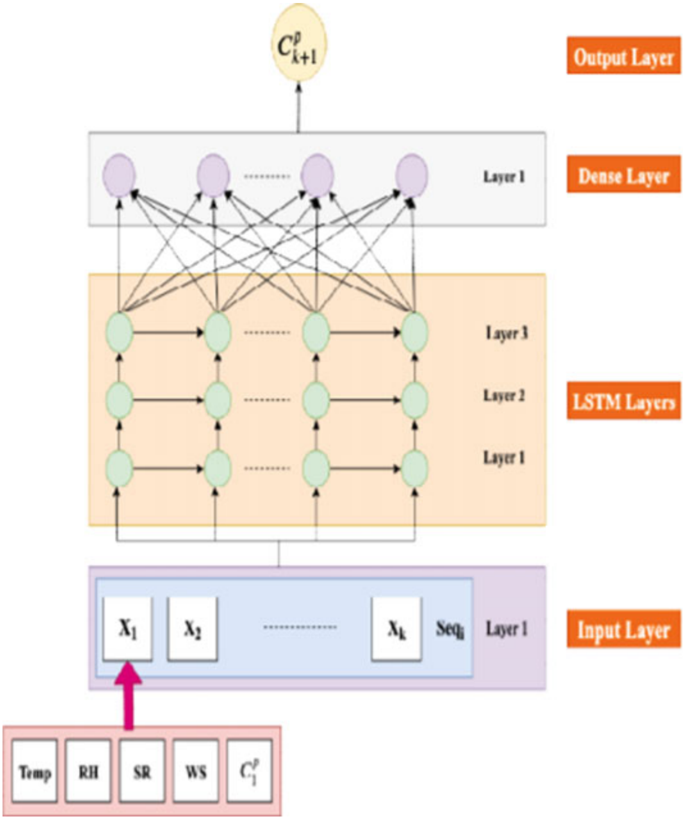

Fig. 14 Model architecture

3.5.2 Mean Absolute Error (MAE)

$$\text{MAE} = \frac{\sum_{i=1}^{n} \left| y_{i_{\text{true}}} - y_{i_{\text{pred}}} \right|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n} \tag{2}$$

3.6 Training Model

Python and Scikit-learn, an open-source machine learning library were used to implement the regression strategies in segment 3. Getting to Jupyter Notebook (an open-source Python supervisor) for programming in Python was done with the Boa Constrictor Guide 5.1, which is a Python data science platform that uses open-source Python data. Each of the stations had three instances, the first being AQI of $PM_{2.5}$, the second being AQI of PM_{10}, and the last being AQI of gases. The nine training data arrangements contained eight regression models prepared for eight sets of training data. According to the US Centers for Disease Control and Prevention, the following correlations exist between the average AQI for $PM_{2.5}$ and the actual AQI. For the remaining eight cases, comparative results were obtained.

4 Experimental Results

Multiple Python packages are used in the development of the proposed LSTM model, including Keras, Scikit-learn, and TensorFlow. In order to standardize data in the 0–1 range, Scikit-learn library uses its Min–Max scaler. For plotting all the graphs, Matplotlib is used in Python. LSTM architecture is governed by multiple variables, such as the number of epochs, batches, LSTM layers, and units per LSTM layer. By adjusting these parameters, the authors aim to balance overfitting and underfitting. Overfitting can also be prevented by using dropout layers. During training, dropout layers randomly remove units from the network, preventing too much coadaptation with the unit. The model is trained using an ADAM optimizer for 20 epochs and 70 batches. The ADAM algorithm is used to train deep-learning models based on stochastic gradient descent. With ADAM's optimization algorithm, dealing with meager slopes and uproarious issues using the most beneficial properties of both Adam Grad and RMSProp algorithms. Most issues with ADAM can be handled with the default setup parameters.

In order to assess the forecast model's health, it is essential to conduct a productive assessment. During the construction of a model, measurements are used for input and to make necessary changes until an appealing exactness is attained or no further advancement of that measurement is possible. In the light of this, the model must be evaluated earlier before it is executed on the test dataset. Different factual measurements are used to assess models as they depend on the objectives of the model, its tasks, and so forth. For example, the authors used mean square error (MSE), mean supreme error (MAE), and R^2 to assess relapse procedures. In Tables 1, 2 and 3, it is shown how the models are presented R. K. Puram, Punjabi Bagh, and Anand Vihar for each instance.

The number of epochs it must run in Fig. 15. As a result, it cycles through all of the data 20 times. In Fig. 16, authors implemented plotting the data to see how the model's loss is decreasing, which is a good indicator as the epochs increase. Figure 17 depicts their efforts in forecasting the data by considering the test data and used it to run the model effectively. As a result, the final result projections are proved to be extremely accurate.

```
Epoch 1/20
126/126 - 1s - loss: 0.0141 - val_loss: 0.0100
Epoch 2/20
126/126 - 1s - loss: 0.0054 - val_loss: 0.0112
Epoch 3/20
126/126 - 1s - loss: 0.0047 - val_loss: 0.0111
Epoch 4/20
126/126 - 1s - loss: 0.0042 - val_loss: 0.0106
Epoch 5/20
126/126 - 1s - loss: 0.0038 - val_loss: 0.0101
Epoch 6/20
126/126 - 1s - loss: 0.0035 - val_loss: 0.0093
Epoch 7/20
126/126 - 1s - loss: 0.0032 - val_loss: 0.0083
Epoch 8/20
126/126 - 1s - loss: 0.0030 - val_loss: 0.0076
Epoch 9/20
126/126 - 1s - loss: 0.0027 - val_loss: 0.0066
Epoch 10/20
126/126 - 1s - loss: 0.0026 - val_loss: 0.0057
Epoch 11/20
126/126 - 1s - loss: 0.0025 - val_loss: 0.0051
Epoch 12/20
126/126 - 1s - loss: 0.0024 - val_loss: 0.0044
Epoch 13/20
126/126 - 1s - loss: 0.0023 - val_loss: 0.0042
Epoch 14/20
126/126 - 1s - loss: 0.0023 - val_loss: 0.0037
Epoch 15/20
126/126 - 1s - loss: 0.0022 - val_loss: 0.0034
Epoch 16/20
126/126 - 1s - loss: 0.0022 - val_loss: 0.0033
Epoch 17/20
126/126 - 1s - loss: 0.0022 - val_loss: 0.0030
Epoch 18/20
126/126 - 1s - loss: 0.0021 - val_loss: 0.0029
Epoch 19/20
126/126 - 1s - loss: 0.0021 - val_loss: 0.0028
Epoch 20/20
126/126 - 1s - loss: 0.0021 - val_loss: 0.0027
```

Fig. 15 History of loss

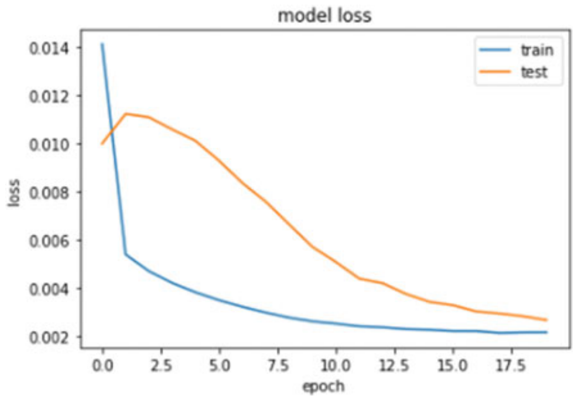

Fig. 16 Model loss graph

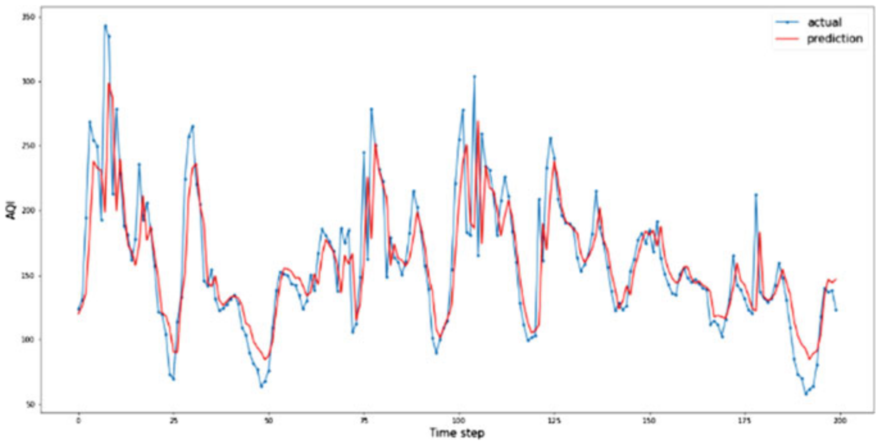

Fig. 17 AQI predicted output

5 Conclusion

Recent advances in the improvement of deep learning models have prompted a fast expansion in their application in scholarly and modern settings. In Delhi, the best natural concern is air pollution as fine PM, which comprises of fluid and strong molecule exacerbates that are hazardous to human wellbeing. Regardless of expanding levels of air toxins in Delhi, the quantity of estimation stations stays inadequate to acquire precise PM levels all through the nation. In this study, authors proposed prescient models of fine PM fixation utilizing LSTM and DAE approaches and thought about their RMSE esteems for 10-day PM10 and PM2.5fixations forecast results for Seoul. The foremost commitments of this investigation are as per the following: (1) As indicated by the trial results, authors have streamlined the LSTM and DAE model with a learning pace of 0.01, age of 20, and cluster sizes of 70. Complete normal RMSE of expectation of PM_{10} and $PM_{2.5}$, the LSTM forecast model was more exact than the DAE model. The examination indicated that the proposed calculation can foresee and get suitable exactness among LSTM and DAE models. Later on, a future study on elective deep learning models can be done to get more precise outcomes with bigger informational collections. The proposed model can be further improvised by considering GIS-based spatial information.

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