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A Dream City: Identifying Red Spots Based On IoT Based Air Pollution Prediction Model

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***Abstract*: The rapid growth of factories severely increase the air pollution with various particulates. Even though every country insists standards for the emission of pollutants, the violation happens continuously. The identification of violation factories is very essential to save the earth. In this paper, we presented a novel Air pollution free Dream City (APFDC) framework which is based on Nonlinear autoregressive neural network along with Levenberg-Marquardt neural optimizing algorithm for the prediction of factories who violate the standards of pollution control board. We process and analyze obtained IOT based BIG data by means of neural network and predicted accurate violated factories as possible. Obtained results from prediction are then optimized by iteration method designed for finding the best possible combination of neural network parameters. Our proposed model pulls out the air pollution severity and provides the guideline for the requirement of strict supervising. We used city pulse database which consist of 8 features including ozone, particulate matter, carbon monoxide, sulfur dioxide, nitrogen dioxide, longitude, latitude and timestamp for the right prediction. The acquired experimental result showed that the proposed method performs better than conventional methods.**

***Keywords*: Air pollution, Neural Network, IoT, Big data.**

1. Introduction

At present, air pollution is the world's serious health risk that has lot of negative consequences in the field of climatically changes, health issues, breathing problems, green house effects, Ozone effects and acid rain. The increase of $CO_{2,}\ CO, N_2$ acidification of lakes and affects eco system. The researchers proclaimed so many air pollution monitoring solutions regarding conventional and Internet of Things (IOT) based monitoring systems. The main drawbacks of conventional monitoring devices are their [1]large size, heavyweight and extraordinarily expensive. The placement of conventional devices plays major role in the monitoring of air pollutants. It's proved that IOT based monitoring system has more advantages than the conventional monitoring systems. Still the IOT implementation suffer with crucial concerns that are a notable barrier for the adoption of the technology. The main barriers could be listed such on [2]multiple sensor devices, indoor and outdoor environments, uneven data sensitivity, Complex spatial and temporal data, Multidimensional exploratory ,data preprocessing and variation analysis. Generally [4] sensors create bulky amount of data within short duration. [5] commercially there are variety of IoT devices which differs in the forms of data formats and semantics. [6]Uncertainty is the major barrier when dealing with IoT data. [7]Particular factory of the urban city continuously emit specific pollutant with a rapid amount. This increases the possibility of the acid rain and severely damages the eco-system. We name these types of factories as a Red Spot. [8]This red spots violate the rules of the pollution control board and damage the lungs of the beautiful urban city. These problems turn out to be solid huddles in the road of IOT based air pollution monitoring system. In this paper, we propose an Air pollution free Dream City (APFDC) framework to Avoid False Alarm in Urban Cities through an enhanced Big Data Processing Model in monitoring air pollution. Moreover, a secure implementation of the proposed APFDC framework is operates based on continuous sensing data analytical module, pollutants deviation module, Event triggering module, Quality validation module and decision support module. In this connection, the objectives of the present investigation were framed so as to assist the monitoring process. The novelty of our research falls in the following statements.

a) An Air pollution free Dream City (APFDC) framework performs a middleware role to aggregate sensing data with high intelligence and spot out the areas that has high concentration of air pollutants in urban cities.
b) Pollutants deviation module verifies the deviation of pollutant results along with spatial and temporal data and determines the red spots.
c) Quality validation module Compare the observed reading data with National Ambient Air Quality standards.
d) Our proposed model maintains the standard to an acceptable level.
e) Validation of the attained results for future implementation.

This remaining section of this paper is well ordered as follows. The section II exhibits the previous work related to air pollution monitoring system, IOT based framework models and related issues. Section III explores the proposed Air pollution free Dream City (APFDC) framework assisted with five modules. The section IV discusses the verification results and

Table 1

Pollutants	Time Weighted Average	Concentration of Ambient Air		
		Industrial Area	Residential Rural	Sensitive Area
Sulphur Dioxide(So_2)	Annual Average 24 hours	80µg m^3 120µg m^3	60µg m^3 80µg m^3	15µg m^3 30µg m^3
Oxides of Nitrogen(No_2)	Annual Average 24 hours	80µg m^3 120µg m^3	60µg m^3 80µg m^3	15µg m^3 30µg m^3
Suspended Particulate matter(SPM)	Annual Average 24 hours	360µg m^3 150µg m^3	60µg m^3 100µg m^3	50µg m^3 75µg m^3
Respirable Particulate Matter	Annual Average 24 hours	120µg m^3 500µg m^3	360µg m^3 500µg m^3	360µg m^3 500µg m^3
Lead (Pb)	Annual Average 24 hours	1.0µg m^3 1.5µg m^3	0.75µgm^3 1.0 µg m^3	0.50µg m^3 0.75µg m^3
Carbon Monoxide	8 hours 1 hour	5.0mg m^3 10.0mgm^3	2.0mg m^3 500mg m^3	1.0mg m^3 2.0mg m^3

its accuracy. The final section concludes the effectiveness of the APFDC framework and footstep for future research.

2. Background and Related Work

This section concerns the existing ideas with different air pollution monitoring methods and the working principles of sensor networks along with the advantages, disadvantages, comparisons and limitations of Internet of Things. Particularly, it spotlights National Ambient Air Quality Standards (NAAQS), IoT Data Collection, IoT Data Analysis, IoT Data Deployment and Operationalization.

A. National Ambient Air Quality Standards (NAAQS) [9]

The growth of industrialization contributes major damage in air pollution. [10]. Environmental protection agency (EPA) set a standard for each and every practice of industries. Table 1 represent the standard values.

Annual Average represent yearly Arithmetic Mean of minimum 104 measurements in a year taken twice a week 24-hourly at uniform interval. 24 Hours Average represent 24-hourly/8-hourly values should be met 98% of the time in a year. Conversely 2% of the time, it may surpassed but not two successive days. On every occasion and anywhere two successive values go over the boundary précised beyond the relevant type, it shall be well thought-out ample, basis to set up regular/continuous supervise and additional exploration

B. IoT Data Collection

Recent research involves in designing optimal middleware architecture to provide the basic functionalities of IOT devices. Various components are integrated to provide Security, process execution, Data transfer and IOT device identification. This portion mainly deals the variety and veracity challenges of IoT data. i.e. collection of IOT data, structuring and unifying IoT data streams. [11]analyzed all the issues and future research directions of Internet of Things (IOT). This work mainly focused the IoT related challenges. This paper list out the issues such on Naming and Identity Management, Interoperability and Standardization, Information Privacy, Spectrum and energy reduction of IoT devices. It shows a guide map to achieve all possible applications through IoT. [12] surveyed several WSN based air pollution monitoring methods and this survey also stated different types of metal oxide gas sensitive sensors and their working principles. It outlined all the threats related to the design of a wireless sensor network for the air pollution monitoring and reviewed the possible existing techniques like Static Sensor Network (SSN), Community Sensor Network (CSN), Vehicle Sensor Network (VSN). Finally, this survey left some challenges pertaining to observance with principles, availability of bandwidth, global execution, Hardware and Software Issues and architecture that need to be addressed.

[13] Proposed three different IoT-based wireless sensors for environmental and ambient monitoring. The first sensor use User Datagram Protocol (UDP) for Wi-Fi communication. The second sensor use Hypertext Transfer Protocol (HTTP), and a third one using Bluetooth Smart. The effectiveness of deployed sensors are validated based on energy consumption, user friendly, solution complexity, and Internet connectivity facility [14]. Proposed indoor Air Quality monitoring architecture using IAQ sensors (SHT10, MQ7, T6615 CO_2, LDR5) and wireless Zigbee protocol for communication. The collected data were sent through wemos integrated Wi-Fi to MySQL database webservices

C. IoT Data Analysis

This section handle the functions of storing, organizing, processing, and sharing the pollution sensed data. [15] introduced a new information integrated system that unite Internet of Things, Cloud Computing, Geoinformatics, geographical information system (GIS), and global positioning system (GPS)] for environmental monitoring and management, This integrated approach proposed four layers namely perception layer, network layer, middleware layer, and application layer to monitor the environment. This research work provided a clear roadmap for future research regarding IOT and BIG data.[16] Used MQ135 gas sensor to sense different type of dangerous gas and Arduino is connected to trigger the alarm which controls the entire process. [17] used Low Power Wide Area(LPWA) technology that cover nearly 20 km range. The architecture consists of sensors, microcontroller unit (MCU) and battery. The sensed data are aggregated with IoT cloud and processed with different types of servers. This work used Access Point for receiving sensor signals and air quality detection. They used Individual Air Quality Index (IAQI) to measure the level of each pollutant. This work deployed Web Socket protocol to provide efficient and reliable communication between the server and clients.[18] Introduced a new concept Pollution to monitor the air pollution using Arduino which is IoT Cloud that involves in managing data coming from air quality sensors. It used twelve gas sensors along with Arduino. This research used REST API (based on user datagram protocol) and MQTT protocol (Machine to machine protocol) for communication of messages. The attained results indicated 47% of power savings and justified as best in terms of both costs and performance.

D. IoT Data Deployment and Operationalization

IoT based Air Pollution Monitoring System will be very beneficial for monitoring different high risk areas of urban city. It will provide real-time information about the level of air pollution in these areas, as well as provide alerts in cases of drastic change in quality of air. [19] Proposed a new idea to monitor Vehicular Pollution in urban cities. This work mainly focus emission of carbon-di-oxide and sulphur related pollutants. The reader system records the sensing data along with RFID tag. The sensed continuous data is sent to the microcontroller for confirmation of the contamination level of the vehicle. The microcontroller verifies the levels of the pollutants of the air produced by the vehicle. If the pollutants levels are beyond the threshold levels, then it sends the warning message to the vehicle owner.[20] Proposed UH-BigDataSys testbed that integrate multi-source air quality data and deployed artificial intelligence in M-AQI big data. Edge cloud based data integration involves in the extraction of location feature and time feature of AQI data. [21] Proposed Long Short Term Memory (LSTM) networks to predict future values of air quality in a smart city. It applied deep learning model with Citypulse dataset. This work used AQI Index to trigger the alarm. [22] Introduced a testbed regarding wireless sensor network monitoring resultant toward automatic and real-time monitoring of environmental pollution. It briefly explained the practical issues in the integration of sensors and actual power consumption rates. This testbed supported the user to change the sleep time of the sensors from the central server depending on the criticality of the situation. Several related work exist regarding air pollution monitoring system and everyone tries to find a better optimal solution. Still there are common problems that increase false alarm rate. There is lot of troubles in weighing pollutant Responses and Dealing with uncertainty. Moreover, there is no proper research for the determination of red spots that suddenly increase the toxic gases to the environment. Our research work can be used as a supplementary tool for the pollution control board to determine the factories who violates the rules of the government.

3. Proposed System

In this section, the IoT based sensed data collection as well as the proposed Air pollution free Dream City (APFDC) framework is presented. The detailed flow of operation is explored in figure 1. Data collection step perform the operations with IOT sensors. In the next Data processing step, SO_2, NO_2 and other air pollutant sensors collect data from each run was processed with analog to digital converter. Figure 1 illustrate step by step description of proposed Framework. Nonlinear autoregressive network train to test data sets with Feed Forward neural structures. The next step involves in optimizing the results correspondent to the best true positive rate. The hidden facts can be predicted about the redspots and expressed. The proposed air quality prediction model consists of four parts. In the first part, IoT data aggregation is realized. The second part involves in the preprocessing of data. Third section explains a deep learning model consisting of nonlinear autoregressive neural networks. Fourth Section trigger the alarm events based on the attained predicted results.

A. IoT Big Data

IoT BIG Data differs from the conventional BIG data based on its heterogeneity nature. IOT BIG Data is time and spatial dependent. IOT streams have very high ingestion rates and Map Reduce is inappropriate. Veracity is very common in the IOT data because of noisy nature of IOT. As part of this phase IoT data are collected and enriched with the proper contextual metadata, such as location information and timestamps. Moreover, the data are validated in terms of their format and source of origin. Also, they are validated in terms of their integrity, accuracy and consistency.

B. Data Preprocessing

Data could be processed straight away exclusive of using any preprocessing methods. In some situation, we require to select the right format of data to attain more accurate and trustworthy results. The existence of mutual relationships should be very clear with the data in order to find the correlations. The spatial and temporal metadata are given as parameter to the training algorithm. The collected data will be represented as a data matrix, consisting of data rows and columns. The columns correspond to the measurement variables. The rows correspond to units of measurement or different points of time.

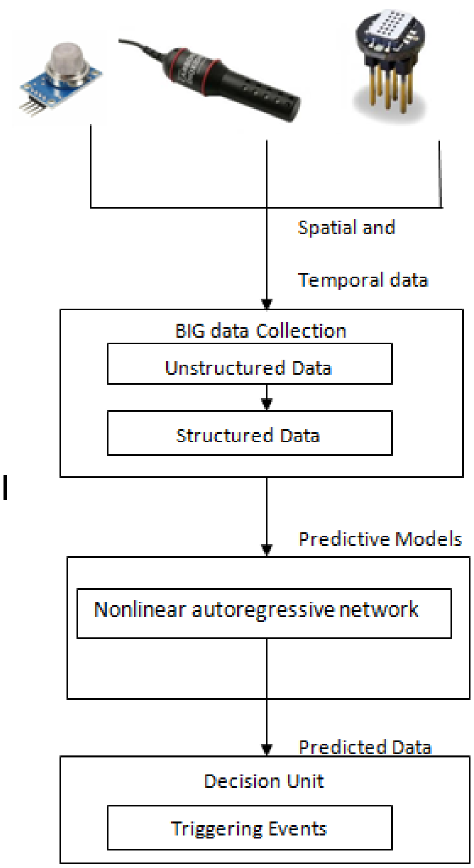

Fig. 1. Proposed framework

C. *Nonlinear autoregressive neural network*

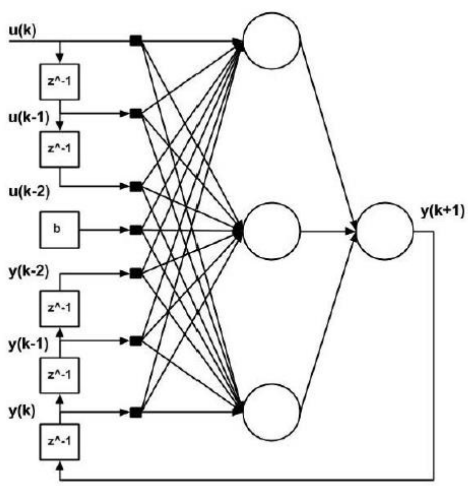

Fig. 2. Nonlinear autoregressive neural network

Red spot predictions are not purely concerned with one-time prediction but a long-term prediction of time series. Long-term prediction faces increasing uncertainties from various sources, including the lack of information about a system's current state. Figure 2 demonstrate the implementation of nonlinear autoregressive neural network. The recursive method employs the predicted pollutant emission values as known data to predict the next possible ones. The sixth estimated values will use the first through fifth examined values as well as the known values of the pollution monitored data to predict the seventh predicted value. Thus Nonlinear autoregressive neural network used to represent discrete time multi-variable non-linear stochastic systems which is derived from the neural network. The input sensed data u(k) is multiplied by the weights w and then the bias b is added. The bias can shift the activation function and change the range of value going towards the output. The activation function use nonlinear autoregressive neural network to determine the peak air pollution areas of the urban cities. This approach is very effective because some pollutants are highly correlated with other pollutant existence. This neural network consists of 3 layers such as input, hidden and output layer. The designed nonlinear autoregressive neural network contains a recurrent connection enclosing several layers of the network. The hidden information (violation) of the factories can be predicted with continuous recurrent network. The output can be achieved from the following equation.

$$y(k+1) = f(y(k-1).\,y(k-2), \dots y(k - n_{y)},\, u(k-1), u(k-2) \dots\dots u(k-n_u))$$

Where the output vector *y(k+1)* is computed as a nonlinear function of the input vector *u(k), u(k-1), …, u(k-du)* which has a predetermined delay. Besides, the output is affected by a recurrent connection *y(k), y(k-1), …, y(k-dy)* that goes from the output back to the input layer.

The nonlinear autoregressive network with exogenous input affords very exact disordered time series prediction that absolutely suitable to find out the red spots of the urban cities.

Figure 2 illustrates nonlinear autoregressive neural network and basic idea to attain the hidden data. Mainly this approach is very suitable for sensors uncertainty data. The nonlinearity and dynamic character allows computing and determining tasks that are almost impossible to solve for conventional methods. For Deep learning process we here apply Feedforward-dynamic networks with recurrent feedback. This recurrent connection allows the network to examine the data associations with improved accurateness. Real time IOT sensing data is not delayed and the recurrent connection is delayed by 1 time step. We use Levenberg-Marquardt algorithm to train the data with small modification. The learning problem works based on loss function minimization. The error is responsible to measure the neural network adaptation of the data set. The loss function depends on the weight parameters of biases and synaptic in the neural network. Levenberg-Marquardt algorithm's loss function depends on sum of squared errors between the target outputs and the network's simulated outputs.

$$e = \sum_{m=1}^{n} \frac{1}{2}(x_m - O_m)^2$$

where O_m is the output for the m-th pattern and x_m is a desired output, n is the total number of training patterns.

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Training Algorithm

Initialize Weights:
While not StopCriterion do
Calculate e(z) for each pattern:

$$e1 = \sum_{n=1}^{n} e^{n}(z)^{X} e^{n}(z)$$

Calculate J(Z) for each pattern
Repeat
Calculate Δ_z
Calculate e2

$$e2 = \sum_{n=1}^{n} e^{n}\,(z + \Delta_z)^{x} e^{n}(z + \Delta_z)$$

If(e1<=e2) then

$$\mu = \mu * \beta$$

Endif
Until(e2<e1)
$\mu = \mu/\beta$
W=z+Δ_z
Endwhile

where the *J(z)* parameter presents the Jacobian matrix, the *e(z)* parameter denotes the error of the network for pattern *p*. The β parameter a factor that increase or decrease the μ parameter which is the most variable parameter called the learning parameter. This parameter varies over the time with iteration process. The type of learning is determined by the manner in which the parameter changes take place.

4. Experimental Setup and Results

A. Dataset Description

We used [23] city pulse database to evaluate all the experiments of this work. The aforementioned dataset contains 8 features including ozone, particulate matter, carbon monoxide, sulfur dioxide, nitrogen dioxide, longitude, latitude and timestamp was used for experiment. The dataset has 17568 samples that are collected at five-minute intervals. Each sample value is given in the form of EPA's AQI standard. We investigate sulphur dioxide and nitrogen dioxide that may be associated with acid rain. We tested our proposed system regarding violation identification and performance parameters were measured separately. Figure 3 describes the proposed research methodology.

It was necessary to train multiple neural structures for each city pulse data set to determine the red spot areas and factories that release more pollutant gases. Only a small section of the data was examined for the training, testing and validation. We trained 10 input sequence data with 3 different hidden nodes and with different delay time lengths, (30- 60, by 5s). During the optimization routine, a neural network was trained to the data section given the hidden nodes and a delay time. The number of trained neural networks for each data set numbered 40 (5 x 8), each independent of one another consisting of different hidden nodes with different weights and various lag sizes. Neural network training identifies the combination of networks that provide the best true-positive rate within each spot location of urban city.

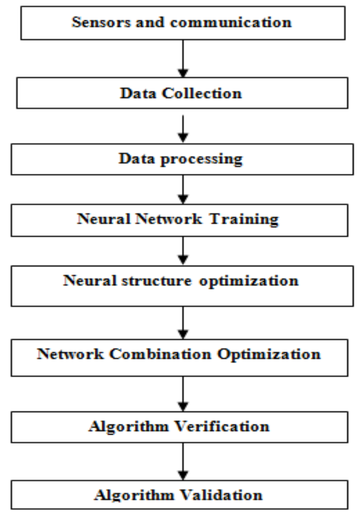

Fig. 3. Research methodology

5. Proposed Model

Proposed model consist of deep learning model with Nonlinear autoregressive neural network.

Table 2

Hyper parameters	Values
Input sequence	10
Hidden layer	3
Output layer	1
Record Size	50
No. Of Epoch	200

The Levenberg-Marquardt algorithm uses momentum learning instead of the learning rate. This method is predominantly useful for obtaining optimized results in larger data sets. The optimized parameters are represented in the table 3

Table 3
Training Parameters

Maximum Epochs	300	μ	0.001
Maximum Training Time	300 Seconds	μ decrease ratio	0.1
Performance goal	0	μ increase ratio	5
Maximum Gradient	1e-7	Maximum μ	1000
No. of validation checks	10		

A. Performance metrics

In order to evaluate our proposed algorithm, we considered accuracy, precision, recall and specificity metrics to assess the efficacy of the proposed Air pollution free Dream City (APFDC) framework. AQI levels are divided into three threshold values by considering AQI critical level (125). These threshold values are defined as alarm color and shown in table 4.

Table 4

AQI Values	Violation level	Indicator
25-75	NO	GREEN
75-125	Moderate	ORANGE
More than 125	YES	RED

Based on this indicator we can assess the violation. The above said performance metrics could be calculated using the following formulas.

Accuracy is defined as a ratio between number of correct predictions and total of all cases to be predicted.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision (P) is the fraction of the predicted positive cases that were correct, as calculated using the equation,

$$Precision = \frac{TP}{TP + FP}$$

Recall or true positive (TP) rate is the fraction of positive cases that were properly acknowledged.

$$TPR = \frac{TP}{FN + TP}$$

True negative (TN) rate is defined as the proportion of negatives cases that were classified correctly.

$$TNR = \frac{TN}{FP + TN}$$

B. *Implementation results*

Air pollution free Dream City (APFDC) framework was applied for the prediction of redspot factories that violate the pollution standard using citypulse dataset. The several performance measures are assessed with the tools of Bigdata.

C. *Comparison results*

This section involves with comparing our APFDC framework with other air pollution prediction methods like Long Short Term Memory (LSTM) and Low Power Wide Area (LPWA) from points of view of accuracy, precision, sensitivity and specificity.

D. *Accuracy*

To compare the efficacy of the APFDC framework, we consider the accuracy parameter measure as first.

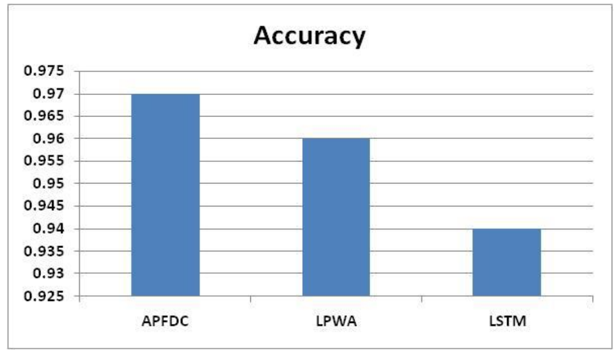

Fig. 4. Comparison results of accuracy measure

Figure 4 exhibit the valuation results of all compared algorithms. Our proposed APFDC framework achieved 0.97 accuracy. LPWA and attained 0.96 and 0.94 values. APFDC achieved only small better accuracy than LPWA and 3% more effective than LSTM technology. This is due to the process of recursive hidden layer information of our framework.

E. *False positive Rate*

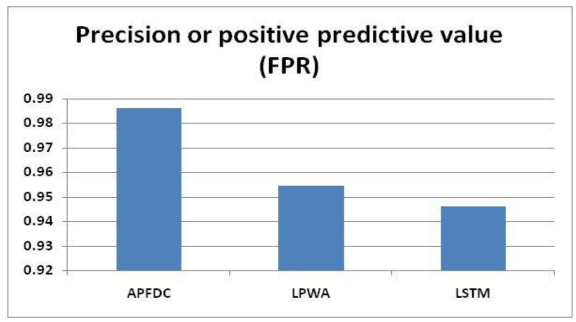

Fig. 5. Comparison results of Precision

Figure 5 shows the precision values for the compared prediction techniques. APFDC framework attained 0.986 precision values and 0.95, 0.94 for LPWA, LSTM respectively. This due to the feature association calculation of every combined interrelated pollutants.

F. *True positive rate*

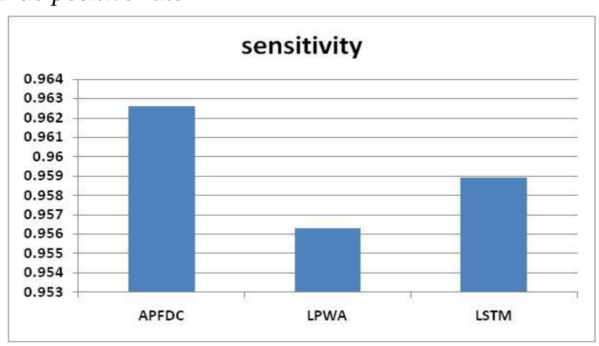

Fig. 6. Comparison results of Sensitivity

The hit rate is measured between real time previous violation history and systematic analysis. Figure 6 illustrates the sensitivity values of APFDC and other methods (APFDC- 0.96, LPWA-0.95, LSTM- 0.95). Our proposed method involves in

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the determination of hidden facts with pre-defined knowledge using recursive correction.

G. True negative rate

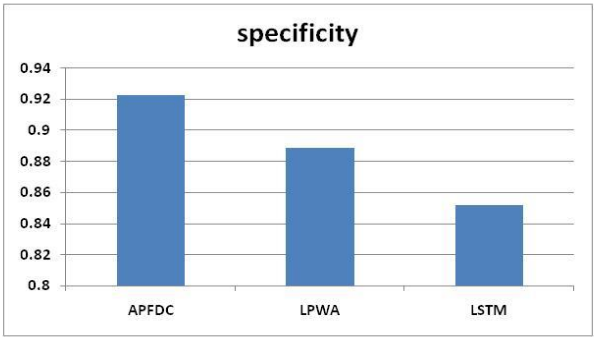

Fig. 7. Comparison results of Specificity

The negative records that outline the emission of sulpur and nitrogen dioxide content could be clearly identified with APFDC framework. If the dataset contains negative data records, (factories without any violation) then it could be easily determined. Figure 7 shows the specificity values. Our algorithm easily determines formal and eco-friendly data records using neuron analyzer. Figure 11 indicates the specificity values as (APFDC-0.962, LPWA- 0.888, LSTMs-0.851) which proclaim the confidence of our APFDC method.

6. Conclusion

In this paper, we presented a novel Air pollution free Dream City (APFDC) framework which is based on nonlinear autoregressive neural network along with Levenberg-Marquardt neural optimizing algorithm for the prediction of the factories who violate the standards of pollution control board. In this method, each factory is represented by a node of input layer. The weights are provided according to the emission gas releases. The hidden layer involves in the determination of future possible increase of pollution. The successful identification of red spot factories was evident when the factories pollutant front data was passed through the neural networks trained to the factory front. The violation of factories is considered as an important factor for the next generation to save the earth. Our proposed model pulls out the air pollution severity and provides the guideline for the requirement of strict supervising. We used citypulse database which consist of 8 features including ozone, particulate matter, carbon monoxide, sulfur dioxide, nitrogen dioxide, longitude, latitude and timestamp for the right prediction. The acquired experimental result showed that the proposed method performs better than the LPWA and LSTM. In our future work, we think to work with fuzzy logic to insist AQI index threshold in the occasion of decision point.

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