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Long Range Radio Technology Implementation on Internet of Things to Detect Particulate Matter at the Community Level and Prediction Using Machine Learning Based Approach

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Abstract

An essential element of smart cities involves augmenting the awareness of key stakeholders and the broader populace concerning air pollution. Currently, numerous air quality monitoring systems are commercially available in the market. However, due to their high cost and limited accessibility, they are not frequently utilized by the public. This research presents a low-cost, integrated LoRa-based wireless sensor network to monitor the air quality and predict future air quality index using Long Short-Term Memory (LSTM) and artificial intelligence (AI) techniques. The suggested system has an indoor and outdoor node administrated by the LoRa (Long Range) network. The indoor sensor node receives information about the air quality, dust concentration, humidity, temperature, and particulate matter through the LoRa network. The nodes' data is sent via full-duplex LoRa modules built with free real-time operating system (RTOS). The indoor node is a master node where multiple outdoor nodes integrated with many sensors can be placed at different places in a community to sense various air quality parameters. Utilizing the things network and adafruit IO as the IoT platform, we have developed a cloud-based data management and analysis tool. The system is designed to operate efficiently with outdoor sensor nodes placed at optimal distances of 4 km from interior master nodes. This configuration enables the system to achieve a coverage area of 8 km, ensuring effective data transmission and analysis. Additionally, the study highlights the most effective machine learning technologies to forecast the Air Quality Index.

Keywords: Air pollution; Particulate matter; IoT; LoRa; Wireless sensor networks.
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1. Introduction

Human health and safety are directly affected by air quality; thus, continuous air quality monitoring is essential to steer towards significant health improvements globally. The World Health Organization states that over 80% of urban residents were exposed to air pollution levels above the recommended limits.[1,2]

Developing nations face challenges in managing air quality in densely populated metropolitan centers due to rapid industrial expansion, urbanization, crop residue burning, and fossil fuel usage. Hence, the key indicators determining people's health status are air quality, duration, and degree of pollution exposure within a given region.[3-6] It is believed that poor air quality, mainly due to particulate matter (PM), poses a considerable threat to global well-being since it predominantly impacts the world's impoverished and unprotected people, who are also the most vulnerable.[7-9] Numerous studies suggested that long-term exposure to $PM_{2.5}$ and PM_{10} can cause chronic respiratory and cardiovascular diseases.[10-14] For this reason, it would be a major step forward in the fight against deadly illnesses if there were portable, widespread, and linked equipment and networks for air quality monitoring and pollutant detection.

The Environmental Protection Agency (EPA) of the United States of America identifies high levels of air pollution as one of the top five environmental challenges that impact public health.[15-17] Many governments worldwide establish and manage monitoring stations to assess air quality and provide public access to the gathered data. These stations are equipped with advanced sensors capable of detecting a wide range of air pollutants.[18,19] However, the high expenses associated with setup and maintenance restrict their use.[20,21] Recent

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advancements in embedded systems, sensors, and networks have enabled it to be possible to provide real-time monitoring and customized healthcare systems to individuals for their usage.[22] On the other hand, these consistent technical advancements allow for the development of smart monitoring systems that increase the quality of life.

The Internet of Things (IoT) is a framework in which everyday things have network connectivity and data-gathering capacities. To allow the ambient intelligence capabilities closely associated to monitoring systems, IoT devices should ideally be everywhere, always on, and always learning about their surroundings. IoT is a viable strategy for constructing healthcare systems. Technological developments allow the definition of more sophisticated tools and the implementation of smart monitoring platforms that provide real-time decision-making data.[23,24] Many scholars have proposed several IoT designs for air quality monitoring that enable open-source technologies for data collecting, processing, and transmission and offer portable computing architectures for real-time data.[25-27] However, traditional air quality monitoring systems that use Zigbee, WI-FI, and other short-range networks suffer from drawbacks such as poor wiring adaptability,power hungry, limited capacity to penetrate obstacles, and limited transmission range.

Table 1 displays a concise overview of some significant works. A city-scale PM monitoring system using LoRa WAN technology[28] was deployed in a major city in the United Kingdom, and the results obtained from sensors were compared with data obtained from government stations. Similar work was reported in,[29] where additional data filtering methods and validation techniques were applied to sensor data. An embedded wearable device was designed to monitor workers' safety at the site, and an edge computing paradigm was implemented to notify the status safety authorities.[30] In another study, A cost-effective pollution monitoring system was proposed to obtain real-time air quality data in Khon Kaen, a city in Thailand.[31] A sensor network with a LoRa node was developed to detect gas leakage events and CO_2 and NO_2 pollutants,[32,33] and deep learning techniques were applied to monitor air pollution. The systems outlined in Table 1 acquire environmental parameters and send them to monitoring systems. However, these systems do not include prediction techniques that can anticipate future pollutant levels using historical or collected data. Thus, the objective of this research study is to develop a particulate matter detection system utilizing LoRa Communication technology in the IoT) and predict the concentration of Air Quality Index (AQI) using Machine learning models.

This paper is organized as follows. In "Related work", we introduce the literature review. The proposed system's circuit design, IoT setup, and software are described in Materials and Methods. In 'Results & Discussion', we evaluated the system's efficacy. In the final section, "conclusion and future scope," we present our conclusions. Concerning air quality monitoring,

2. Related work

This section focuses on studies related to wireless sensor networks and air quality monitoring systems. A low-cost system with Zigbee as communication network is proposed in Ref. [34]. The architecture employs fog computing system and artificial intelligence algorithms to enhance the performance of compounds and minimize the presence of pollutants. However, Zigbee is short-range communication and cannot be practical for deploying a system in a large area. Another approach utilized a four-node system composed of controller, XBee transmission module, and Zigbee as the network design in Ref. [35]. Implementing LoRa as Communication network, Y. Ma et al. proposed a real-time pollutant concentration monitoring system.[36] The limitations of the system are data loss as the distance between the nodes increases. Long Range (LoRa) technology is used in another study.[37] to collect and share data from geographical points through a joint sensor network for tracking pollution in smart towns. The drawbacks are that other major air pollutants were not monitored except CO_2, humidity, and temperature.

LoRa communication, which aims to overcome the

Table 1. Short summary of relevant research in air quality detection.

References	MCU	Sensors	Architecture	Low cost	Connectivity	Data Access
Steven J. Johnston *et al.*[28]	Raspberry pi	PM Sensors & DHT22	WSN/IoT	✓	Open VPN & SSH	Desktop
Ueli Schilt *et al.*[29]	ESP8266 / FiPy	PM Sensors, O_3 , NO_2, CO_2 Sensors and DHT22	IOT	X	WiFi/ LTE/LoRa	Desktop
Thanpitcha Atiwanwong & Saweth Hongprasit[30]	ESP32	BMP180, PM Sensors	IOT	✓	WiFi/ LPWAN	Desktop
Pietro Battistoni *et al.*[31]	Rasberry pi/ ESP32	ADLX345	PAN/IoT	X	BLE/WiFi	Mobile
Jovan Kalajdjieski *et al.*[32]	NA	AQ sensors	IoT	X	WiFi	Desktop
Jiang, J.W *et al.*[33]	STM32	DHT22 & CO_2 Sensors	IoT	✓	LoRa	Memory Unit

transmission limitations of Bluetooth, Wi-Fi, and ZigBee, has been extensively proposed and integrated into various designs.[38] Yet, the suggested model is relatively basic and may not satisfy the demands of a large-scale wireless sensor network system. An alternative approach[39] suggested a WSN network in which sensor nodes are equipped with cameras, and Android applications would detect heavily polluted routes and alert the user. However, hazardous contaminants have not been mentioned in the work. Also, the study did not define the most critical aspects of a WiFi-based WSN, including the transmission range and the expected lifespan of the sensor nodes. Another research[40] presented a system for monitoring internal air quality using sensors and a machine learning method by providing users with access to a portal and a mobile app. In addition, Long Short-Term Memory (LSTM) was used to predict future pollutant concentrations. Nevertheless, the outcomes obtained in the air quality categorization were based on indoor air quality and may not apply to an outdoor environment, which many other aspects influence.

3. Experimental Setup and modelling

This section presents the proposed system paradigm for outdoor air quality monitoring using LoRa communication. The overall system architecture is shown in Fig. 1. The sensing node uses ESP32 as the Microcontroller Unit and LoRa as the wireless communication module, and to monitor the particulate matter, the system uses MQ135, a dust sensor with $PM_{2.5}$ & PM_{10}, and DHT22 Temperature and humidity sensors. The temperature sensor has a single-bus communication range of -55 to +125 degrees Celsius, an accuracy of 0.5 degrees Celsius, and a humidity range of (-0 to 99.9%) with an accuracy of 2% relative humidity. The outdoor sensing node acquires ambient parameters regularly and sleeps during non-acquisition times. The ESP32 terminal, which is a monitoring terminal, primarily retrieves the sensor data sent by the sensing node through the LoRa wireless communication module. The microcontroller's system clock ensures that all nodes have appropriately connected and then analyses the data that has been received.

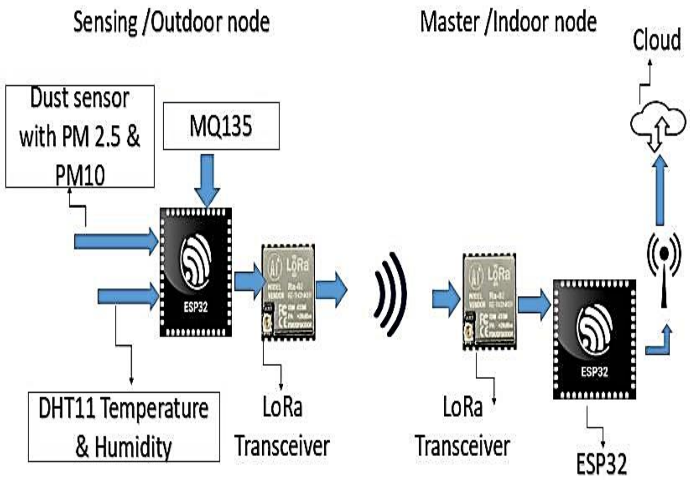

Fig. 1 Overall system architecture.

3.1. Circuit Design

Two distinct circuits comprise the system, with the first serving as a sensor node that records relevant environmental parameters. The other circuit is the master unit's circuit, which manages the data from all sensors and uploads it to the Thing Speak cloud. Figs. 2 & 3 show the complete circuit of sensing and master nodes. MQ135 sensor, DHT11, and dust sensors are connected to the 8th, 10th, and 13th pins of ESP32. A LoRa Module connected to ESP32 communicates and transmits the data. Similarly, the master node is connected to the I2C LCD for serial communication. An Arduino Nano interfaced to a memory unit is also connected to the master node to save the collected data.

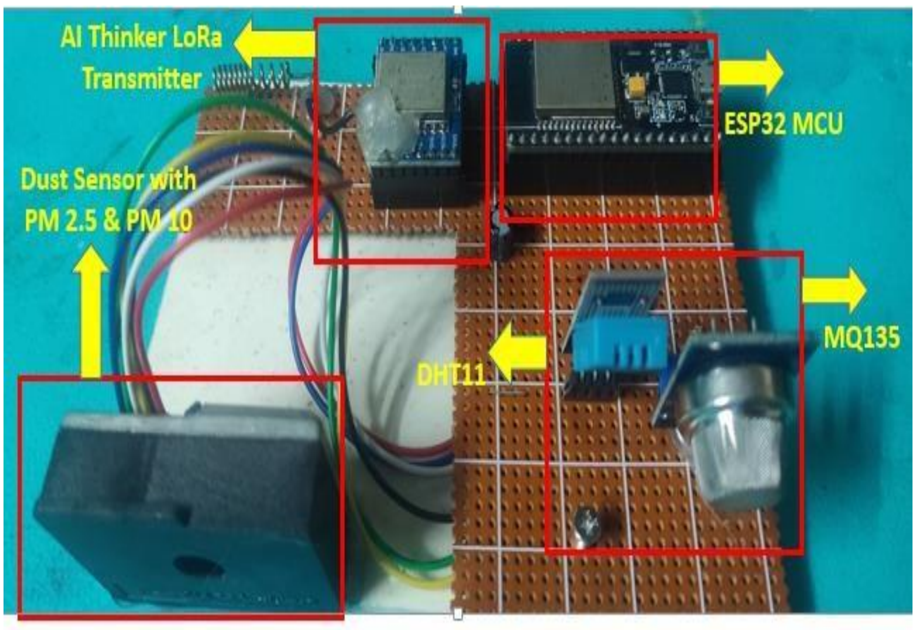

Fig. 2 Sensing node.

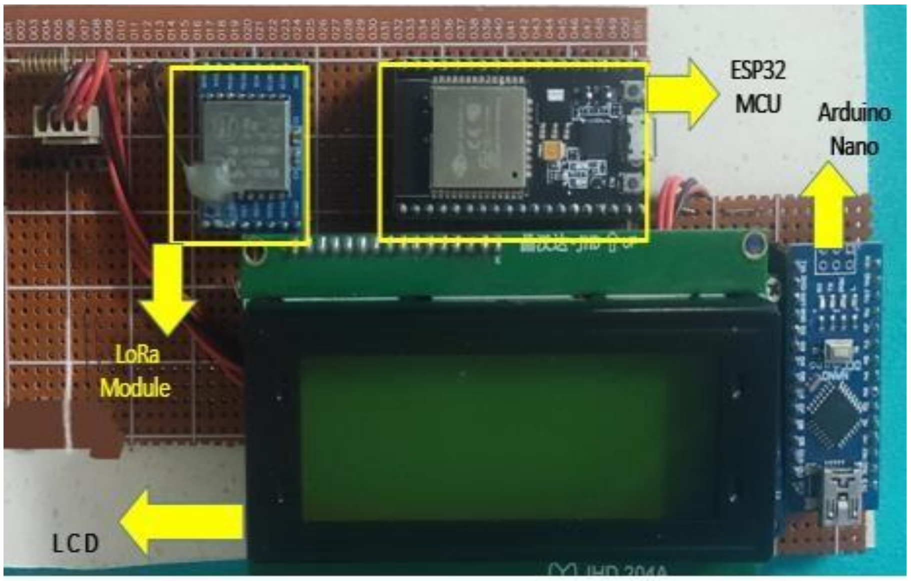

Fig. 3 Master node.

3.2 Software Development

Most projects need the use of many types of software to simulate and analyze the hardware setup. This procedure helps the project participant debug and analyze the project's configuration and outcome. Compiling and uploading code can be attained by Arduino IDE Environment. The present work uses protein and solid results for simulations and 3d design.

3.3 IoT Setup

Things speak IoT Analytics platform services are used in this project. Implement a system with cloud-connected sensors for real-time monitoring of the things network allows the users to create channels and feeds to each environmental parameter. The Things Speak is a global collaborative network of IoT that enables all members to connect their respective networks to a single Internet. Without relying on third-party service providers, developers can construct their apps with the support of the open LoRa community. This study created a dashboard with three feeds to monitor the indoor master node. The dashboard displays temperature, humidity and dust concentration parameters upon establishing a connection between the LoRa device and the Things Speak network. The parameters, as mentioned earlier, are depicted in the form of graphs. A higher AQI number indicates better air quality. Fig. 4 illustrates real-time data of indoor master node parameters. One of the powerful features that we utilize in Things Speak is data statistics. At Things Speak, the scripts are developed using Node.js. These scripts perform AQI computation and report generation.

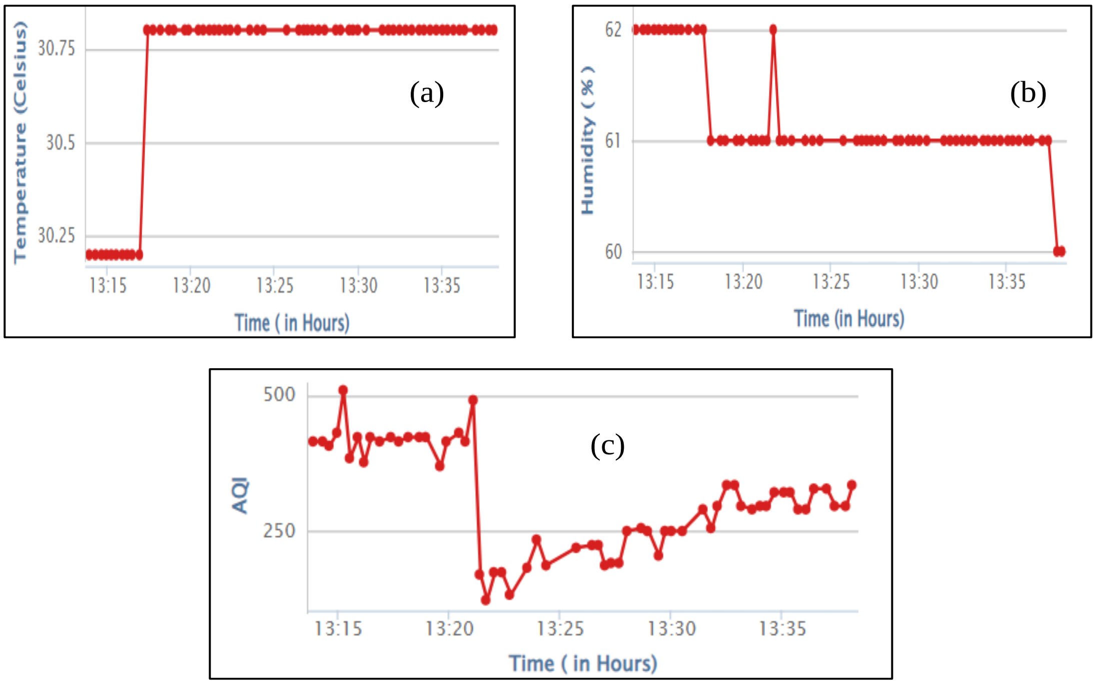

Fig. 4 Things Speak dashboard interfaced with the master node displaying a) Temperature, b) Humidity c) AQI.

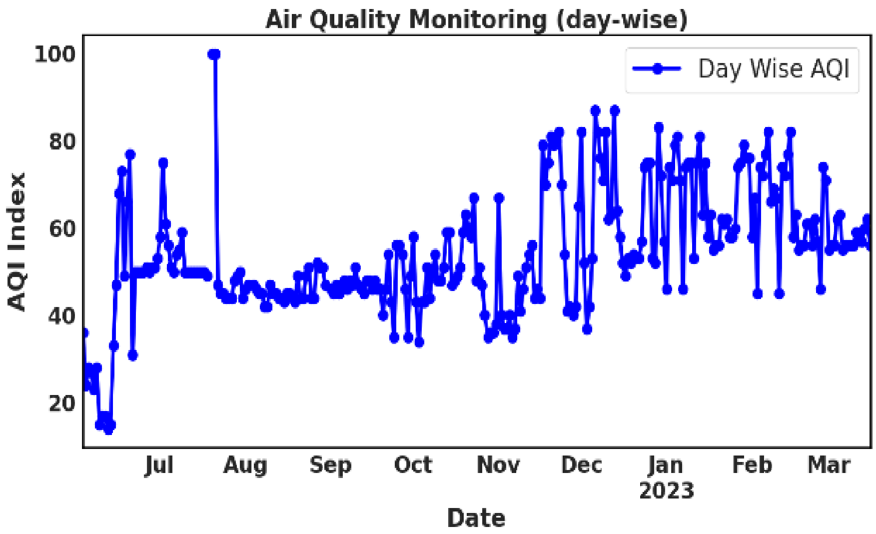

Fig. 5 AQI day-wise trend.

The stored data can be exported in CSV format to any email address. Furthermore, all the real-time dashboard designs can be displayed on smartphone interface. Thanks to Things Network for its reliable data monitoring process and user-friendly interface. Fig. 5 depicts the measured variations in AQI values over time.

3.4 ML-based time series modeling

3.4.1 Naïve bayes model

The Naïve Model is an essential and intuitive foundational method utilized in time series forecasting, specifically when dealing with continuous data sets. In contrast to complex predictive models, the Naïve Model functions using the simple assumption that the value of the subsequent time step will be identical to the value of the time step immediately preceding it. It does not require an intricate training procedure. Due to its usage of the previous time step value without altering the parameters to anticipate the future time step value, it does not need any training. According to this forecasting approach, we expect this period to be the same as the prior period.
Mathematically,

$$\hat{Y}_{t+1} = Y_t \quad (1)$$

where $\hat{Y}_{t+1}$ denotes the predicted value for the subsequent time interval. Y_t denotes the observed value representing the measurement obtained at the present step.

3.4.2 Artificial Neural Network

An artificial neural network comprises a minimum of three interconnected layers, with the first layer representing input neurons that receive data related to the Air Quality Index (AQI). These input neurons transmit AQI information to subsequent layers.[41] The following layers, including hidden layers, process the AQI data and convey the final output, corresponding to the predicted AQI value, to the ultimate output layer. Each layer's connection between neurons is assigned a weight, with the result calculated by multiplying each AQI input by its corresponding weight. The multilayer perceptron network structure involves input layers, hidden layers processing AQI information, and an output layer predicting the AQI value.

An equation that illustrates the connection between the AQI inputs $(y_{t-1}, y_{t-2}, \dots \dots, y_{t-p})$ and the outputs (y_t) for MLFFN

$$Y_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i f\left(\sum_{i=1}^{p} \beta_{ij} Y_{t-1} + \beta_{0j}\right) + e_i \quad (2)$$

Here 'αi' denotes the weight from the hidden to output nodes, and 'β.j' is the weight from the input to hidden nodes; 'f' is the activation function.

3.4.3 CONV1D (1D Convolution Layer) neural network

A CNN is useful for finding basic patterns within large amounts of data, which may subsequently be used to form more complicated patterns inside higher network layers.[42] The convolution layer is responsible for extracting features from the AQI data. In the dense layer, the output was generated using the data from the convolution layer.
In each CNN1D, forward propagation is expressed as follows.

$$y_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} \mathrm{conv1D}(w_{ik}^{l-1}, s_i^{l-1}) \quad (3)$$

where y_k^l is defined as the AQI input, b_k^l is defined as the bias of the kth neuron at layer l, s_i^{l-1} is the output of the ith neuron at layer l - 1, w_{ik}^{l-1} is the kernel from ith neuron at layer l – 1to the kth neuron at layer l.

3.4.4 RNN (Long short-term memory)

The Recurrent Neural Networks (RNN) model is a prevalent technique for time-series forecasting, offering superior benefits compared to other neural network models when handling time sequence data.[43] In an RNN, the output of the previous step is used as input in the stage being processed. Gradient disappearance is an RNN limitation, especially when handling enormous time series data.[44] However, A form of recurrent neural network known as a "Long Short-Term Memory" (LSTM) network shown in Fig. 6 is capable of

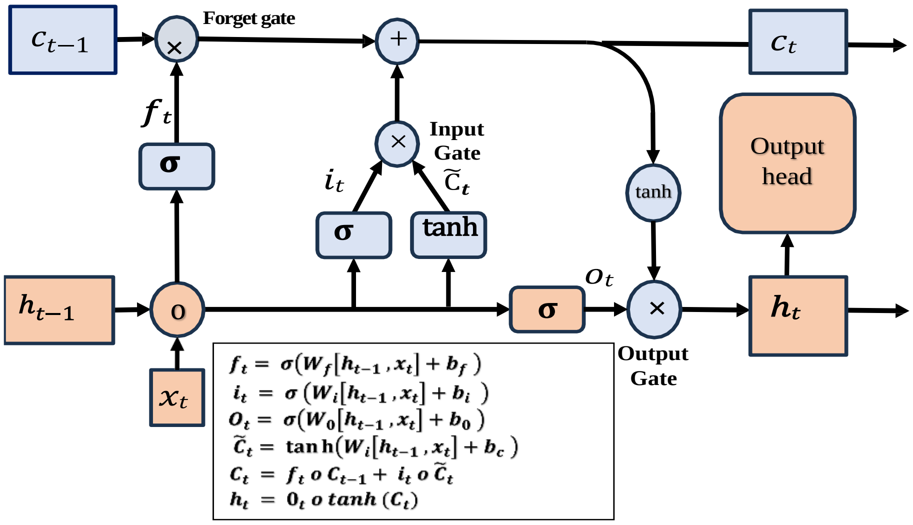

Fig. 6 RNN- LSTM model.

learning order dependency in sequence prediction problems.[45] The LSTM data structure is organized as a chain and comprises four neural networks and various memory units referred to as cells. The cells are responsible for information storage, whereas the gates control memory processing. They store information about previous inputs for a period that is not predetermined as a priority but rather determined by the weights of the information and the data that has been received. Therefore, LSTM is a cutting-edge time-series prediction method.[46]

In recent times, due to the unpredictable and dynamic nature of the pollution, precisely forecasting AQI indices has become crucial for effectively communicating both present and predicted levels of air pollution to the public. In this context, we have applied time series modeling techniques such as Naive, ANN, CNN, and LSTM models to AQI indices generated by the LORA network and compare various models using statistical metrics, such as RMSE and MAPE, for all models to obtain optimal results.

4. Results and discussion

This section presents the results of the predicted Air quality index using the LSTM approach. First, we describe a Real-Time Experimental setup to monitor various environmental parameters. The outdoor node was deployed in Hyderabad city

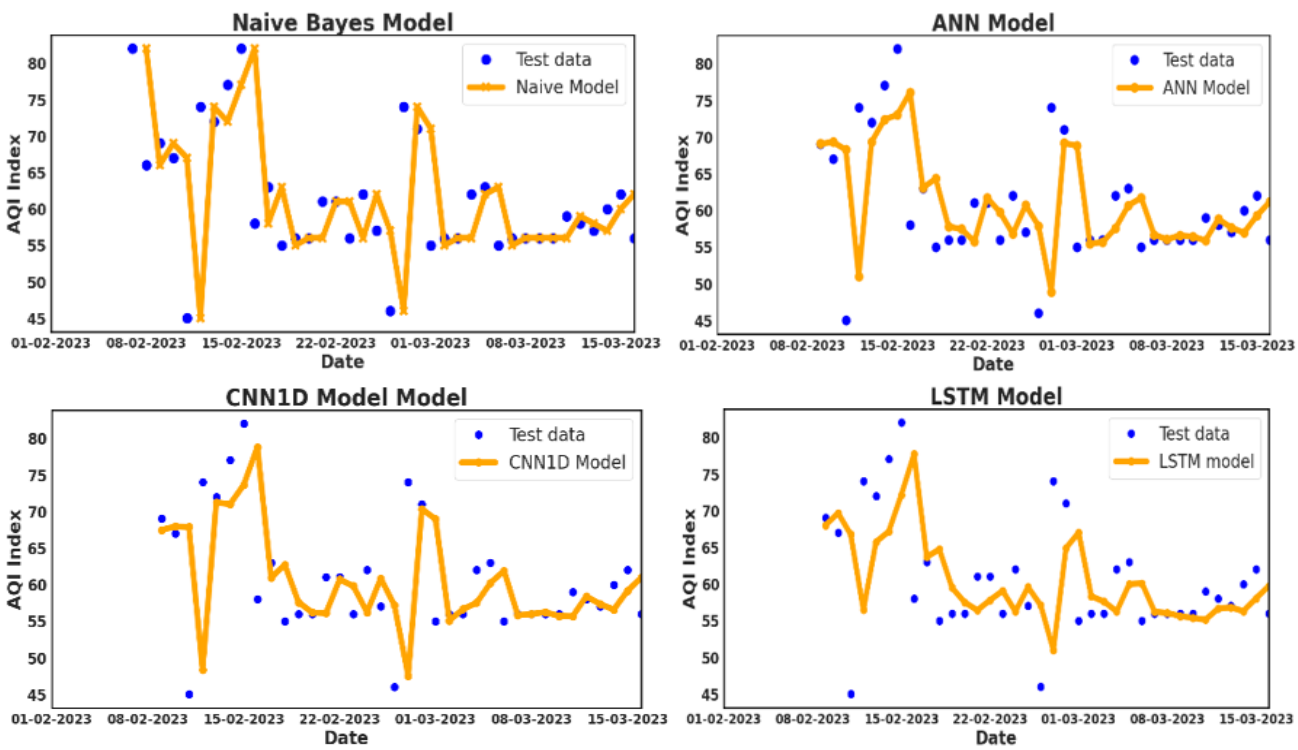

Fig. 7 Actual Vs Predicted AQI level for various models. a) Naive Bayes b) ANN c) CONV1D d) LSTM.

Table 2. Comparison of all algorithms in Air quality detection.

	MAE	MSE	RMSE	MAPE	MASE
Naive Model	6.333333	102.157898	10.107319	10.356464	0.985185
ANN Model	6.030898	89.509178	9.460929	9.935493	0.921387
Conv1D	6.086211	85.611290	9.252637	9.922723	0.929838
LSTM	6.042634	79.151634	8.896720	9.799394	0.923180

in a moderately polluted area approximately 4 km from the master node. The entire system was powered for a few hours daily and we could transmit the data successfully. The subsequent section describes the various deep learning models we used to forecast future Air Quality Index data.

A comparison between the actual and predicted outcomes of the numerous Machine Learning models can be seen in Fig. 7. This study utilized the open-source, high-level deep learning platform Keras. On the basis of equations (1), (2) and (3) the AQI value has been predicted. Fig. 6 concludes that the LSTM Model is closer to the test results after applying all of the Machine Learning models, including Naive Bayes, ANN, CONV1D, and LSTM models, and the benchmark comparison results in Table 2 indicate that the LSTM produces the most effective score performance among the four machine learning models.

We can find the best model architecture to use by trying out several modeling approaches. In contrast to all the models, the single-layer LSTM model gives the best prediction. In LSTM, First, we use the validation data to determine the optimal hyperparameter values (optimizer, initial learning rate, and batch size). The LSTM architecture is tested with six models of varying sizes (10, 30, 50, 100, 150, and 200 neurons), optimizers (Adam), learning rates (0.1, 0.01, and 0.001), and batch sizes (4, 8, and 16). Models are run ten times for each hyperparameter setting before determining an RMSE. Based on the RMSE score on the validation data, the optimal set of hyperparameters for the given model is selected. According to this data, the Adam optimizer's 0.001-rate learning and 8-batch size provide an RMSE of 8.896720, the lowest number in the table. For this reason, we use the Adam optimizer with a learning rate of 0.001 and a batch size of 8 to train the 10-neuron model at full scale to predict the AQI index. As a result, it was used to forecast the AQI indices for the next one year, as shown in Fig. 8.

5. Conclusions

The present study details the development of a sensor network utilizing LoRa technology, which is both cost-effective and energy-efficient and can be easily expanded to accommodate a larger scale. The network is designed to integrate IoT and AI techniques to monitor and predict particulate matter at the community level. To carry out our analysis, we analyzed data from dust sensors, including $PM_{2.5}$ and PM_{10}, carbon monoxide (CO) sensors. The Air Quality Index was predicted using various deep-learning models trained with this data. The LSTM model has demonstrated superior predictive performance, and as illustrated in Fig. 7, the prediction

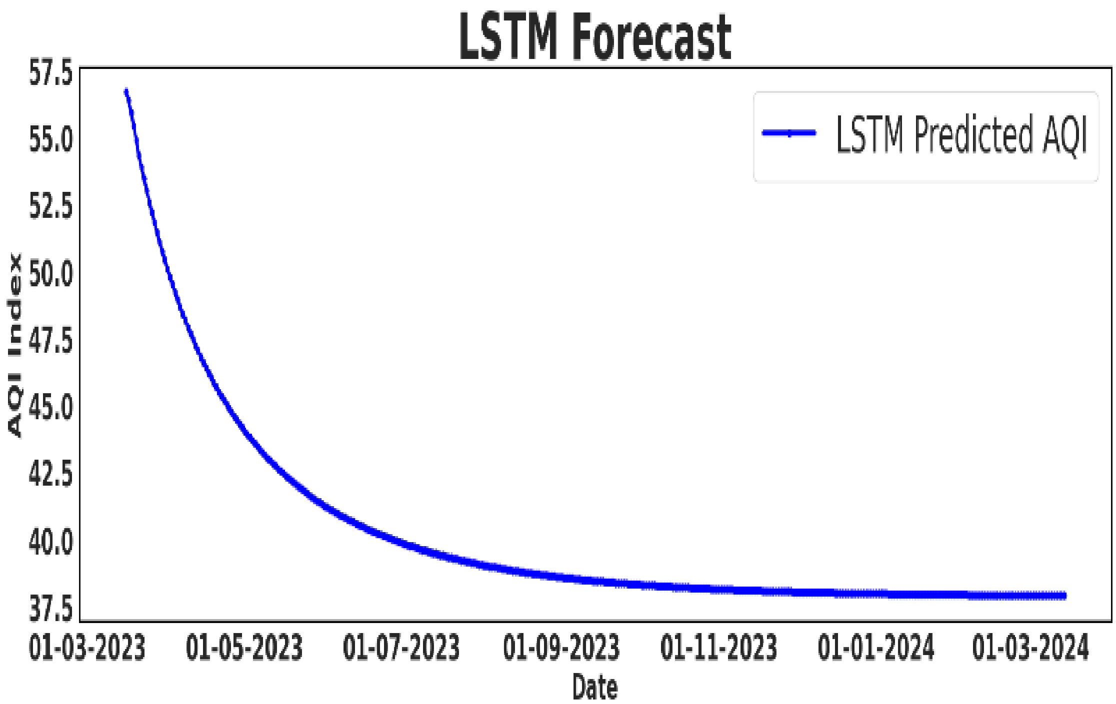

Fig. 8 Predicted AQI level using LSTM model.

suggests that a reduction in AQI values corresponds to an enhancement in the air quality. However, the readings' precision and reliability depend on frequent calibration and maintenance of the sensors, which is a drawback of our study. In forthcoming research, further parameters, including Co_2 and No_2, will be considered to effectively examine their correlation with the Air Quality Index and improve precision. Additionally, the inclusion of multi-step LSTM prediction as a training step can serve to augment the precision of the model. Further validation measurements can be conducted by deploying our suggested outdoor sensor nodes close to a reference station. The deployment of low-cost LoRa-based sensor nodes presents an opportunity for acquiring a more comprehensive set of air quality data within communities at a significantly reduced cost compared to existing fixed, high-precision stations.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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