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AIRO: Development of an Intelligent IoT-based Air Quality Monitoring Solution for Urban Areas

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Abstract

Air pollution is the contamination of the atmosphere by any biological, physical, or chemical means. Bengaluru, the Silicon Valley of India, has air pollution levels that exceed WHO standards. Its air has high PM10, PM2.5, SO2, NO2, and CO2 levels, exposing residents to an increased risk of respiratory diseases. AIRO, a decentralised IoT-based air quality monitoring solution, is proposed to calculate the (Air Quality Index) AQI in real-time and notify the users of dangerous AQI levels. Unlike the city's fixed air quality monitoring stations, this portable system can easily be integrated into everyday items for computing real-time air quality at any given place. The proposed solution is then validated using a physical prototype incorporated into a water bottle. Using the Intel Edison development platform, this prototype is equipped with a GPS module, Wi-Fi module, PMS5003, MQ131, MQ135, MQ136, MQ7 sensors, and an LCD Display. The prototype records the air quality indicators, calculates the AQI, and sends the data to the AWS Cloud Server. After an in-depth analysis of the cloud data, the daily and weekly AQI is predicted for multiple locations in the city. A hybrid CNN-Bi-LSTM model is proposed for predicting AQI, which needs to be evaluated at the city scale for dependable results. Finally, a smartphone app is developed using Android Studio and Python to monitor the air quality and notify the users. The users also have an option to select a location and get the real-time and predicted AQI. In the future, this hybrid deep-learning model can be extended to other cities using the transfer learning approach.

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Keywords: Internet of Things (IoT); Air Quality Monitoring; Deep Neural Network; Design; Artificial Intelligence.

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1. Introduction

Air pollution is the contamination of the environment by any biological, physical, or chemical means that modify the characteristics of the atmosphere. In the Indian subcontinent, more than 51% of the population breathes air that exceeds WHO guidelines (>35 μg/m^3) and while 31% are exposed to air quality in the range of 15–35 μg/m^3[1]. Bengaluru, India's Silicon Valley, has poor air quality due to extensive urbanisation, industrialisation, and vehicle traffic. The geographical expansion, demographic growth, deforestation, and encroachment of Bengaluru water bodies have adversely impacted its environment. Urbanisation aggravates pollution and creates traffic congestion which, in turn, degrades the air quality. Air pollution causes respiratory diseases like coughing, shortness of breath, wheezing, stroke, chest pain, lung cancer, asthma, and heart attacks [2]. In India, the number of premature deaths from ambient air pollution was one million in 2015, while another 1 million deaths were caused by household pollution [3]. The entire population of India is exposed to unhealthy levels of ambient PM_{10}, $PM_{2.5}$, SO_2, O_3, CO_2 and NO_2, which are the major pollutants causing disease and death worldwide. With population explosion and rising fossil fuel consumption, the problem of air pollution is only going to increase in the years ahead. Many cities are installing centralised air quality measuring devices to mitigate air pollution at traffic junctions and industrial areas. Karnataka State Pollution Control Board (KSPCB) has installed seven Continuous Ambient Air Quality Monitoring Stations (CAAQMS) in Bengaluru [4]. These monitoring stations track PM_{10}, $PM_{2.5}$, SO_2, NO_2, Ammonia, O_3, CO, and Benzene on a 24-hour basis. The CAAQMS results are compiled statistically and sent to the Central Pollution Control Board (CPCB), which monitors the Air Quality Index (AQI) of different cities across India.

A thorough market analysis of four air quality monitoring (AQM) devices was conducted. **Table 1** compares these AQM devices based on their technical specifications, design characteristics and cost-effectiveness. Most of the portable air quality monitoring devices available in the market are expensive and are not modular. They do not offer crucial air quality indicators like AQI, O_3, and CO values, do not have IoT capabilities and are not integrated into any smartphone applications. The existing centralised solutions offered by the KSPCB are not useful since most measure the outside air quality. They are centrally located and installed at busy traffic intersections. They are costly and difficult to install in remote locations because they are not portable or modular. The CAAQMS does not provide access to real-time air quality data because its calculations are based on a 24-hour average.

An extensive literature review was conducted to learn more about the various air quality devices developed in the published articles. Although AirSense, developed in [5] includes embedded sensors like GPS, accelerometer, and dust sensor, it only measures $PM_{2.5}$. This device cannot be considered a true air quality monitoring solution since it does not provide comprehensive and real-time information on the air pollutants in indoor and outdoor environments. The IoT-enabled device in [6] only measures CO and HCHO; however, the researchers could not measure CO_2 and other gases. Reviews of both of these products indicate that the developers did not provide a smartphone application for forecasting the real-time AQI. These solutions are unreliable and insufficient because they fail to consider the five major air pollutants in the environment. Hence, a robust air quality monitoring solution is needed to measure and forecast air quality in real-time.

According to [7], the air pollution forecasting methods can be divided into two categories: a) deterministic and b) stochastic. Deterministic methods are model based, which require prior knowledge and multiple input data. These methods are highly complex, exhibiting several use constraints [7]. Stochastic methods include Autoregressive Integrated Moving Average (ARIMA) and Support Vector Machine (SVM) based on historical data for forecasting air quality and are widely used. Since IoT-based decentralised sensors generally capture a lot of data from various locations[8], these traditional statistical methods cannot predict the AQI accurately. Predictions can be more precise by leveraging machine learning, data mining, and artificial intelligence. Random Forest (RF), Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Multiple Linear Regression (MLR), are the most widely used machine learning algorithms for AQI predictions. Long short-term memory (LSTM) is one of the most promising Recurrent Neural Networks (RNN) for air pollution prediction due to its superior performance on time series data [7].

This paper proposes a decentralised air quality monitoring solution to address the above-mentioned challenges. The proposed solution is decentralised, giving real-time AQI information and predicting the expected AQI at a particular location. Moreover, this solution is portable, lightweight, and modular to be integrated into everyday objects. For easy information dissemination, a smartphone application that displays the AQI after gathering data from numerous users from various sites is developed. A backend team analyses the data and manages the smartphone application to predict the future AQI through the acquired air quality data. A smart and energy-neutral IoT sensing device [9–11] with advanced deep learning capabilities that stores data in the cloud is proposed to support this concept; however, this device will need extensive testing in the future [12]. Bi-directional LSTM has captured the attention of many researchers as it captures space-time patterns efficiently while making accurate predictions for time-series data [13]. Some researchers [14–17] have attempted the integration of 1D CNN and LSTM for accurate and robust predictions. However, the complexity of spatiotemporal datasets, incomplete data, and the inability to process data from decentralised mobile devices necessitates a novel approach to integrate 3D CNN to bi-directional LSTM, which is attempted in this study.

This paper is divided into five sections. Section two describes the methodology for developing the proposed air quality monitoring solution. A working prototype is developed and tested in section three, and the preliminary test results are reported. This section conducts a user survey to gather the requirements and finalise technical specifications and product development. Moreover, the AIRO framework is compared with the existing frameworks, and air quality data from several locations in Bengaluru is collected. Section four presents the AQI calculations, proposes a deep CNN-Bi-LSTM hybrid model to forecast the AQI, and develops a business model for AIRO. Finally, section five concludes the paper.

Table 1: A comparative market study of air quality monitoring devices in India.

Products→ **Features ↓**	*Temtop M200™ Air Quality Monitor*	*Prana Air™ Air Quality Monitor*	*INKBIRDPLUS™ Air Quality Monitor*	*Smart™ ZigBee Air Quality Monitor*	*CAAQM Centralised Air Quality Monitoring Stations*
Measures	PM2.5, PM10, CO_2, HCHO, Temp, Humidity	PM1, PM2.5, PM10, AQI	CO_2, HCHO, TVOC, Temp, Humidity	Formaldehyde, VOC, CO_2, temperature, humidity	AQI, CO, NO_2, NH_3, SO_2, PM2.5, PM10, Benzene, Temp, Humidity, etc.
IoT capability	No	No	No	Yes	No
Smartphone app	No	No	No	Yes	Yes
Price	\$320	\$67	\$70	\$84	\$1.8 million
Dimension L×B×H (cm)	13.7 × 7.4 × 3.5	6.7 × 4.3 × 3.4	10 × 8 × 3.5	9.5 × 9.5 × 4	2700 × 1800 × 400
Weight	408g	200g	141g	96g	> 20000 g

2. Methodology

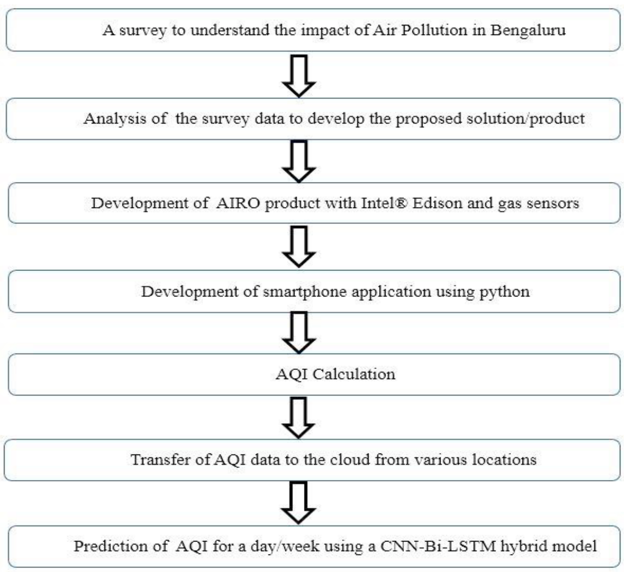

Fig.1. Methodology of the study

A 7-step methodology is followed to develop an air quality monitoring solution named AIRO. A survey was conducted in Bengaluru to understand the impact of air pollution and the usefulness of developing an air quality monitoring solution. Based on the survey, the design specifications are formulated for the proposed air quality monitoring solution. A prototype for AIRO is built on Intel® Edison with a GPS module, Wi-Fi module, MQ131, MQ135, MQ136, MQ7 sensors, and an LCD Display. The sensors embedded in AIRO to measure different pollutant concentrations are MQ131 for detecting O_3, MQ135 for detecting NO_2, MQ136 for detecting SO_2, and MQ7 for detecting CO. The values collected through these gas sensors are sent to the Intel® Edison, which calculates the AQI at a location and is displayed on the device's LCD screen. These values are sent to the AWS cloud database. AWS cloud database sends the various values as input to a proposed CNN-Bi-LSTM hybrid model, which predicts the AQI of any given location.

3. Results

3.1. Survey Results

A survey was conducted among 20 Bengaluru citizens through *Google Forms* to identify the need for a decentralised air monitoring solution. Most of the respondents are not using any application to measure the air quality of their locality and do not use an air purifier in their homes. Hence 60% of respondents felt a need for a device measuring indoor air quality, as shown in **Fig. 2**. According to **Fig. 3**, if a decentralised air monitoring system were priced between ₹ 1000–5000 (~ $12–63), 85% of respondents might be willing to purchase it. Most people reported respiratory diseases like allergies (45%), sinusitis (20%), chest congestion (10%), Conjunctivitis (10%), and other conditions (40%), as shown in **Fig. 4**. Also, 60% of respondents believe that using a smartphone app that forecasts air quality will improve their quality of life.

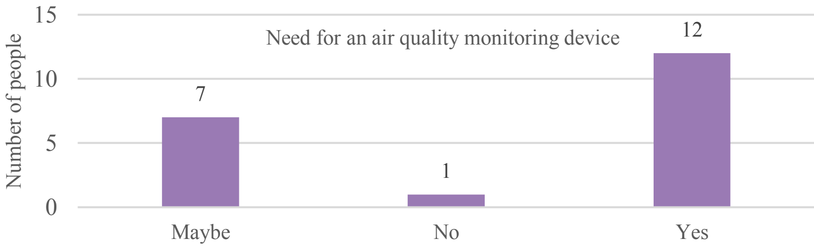

Fig.2. Survey results indicating the need for an air quality monitoring device.

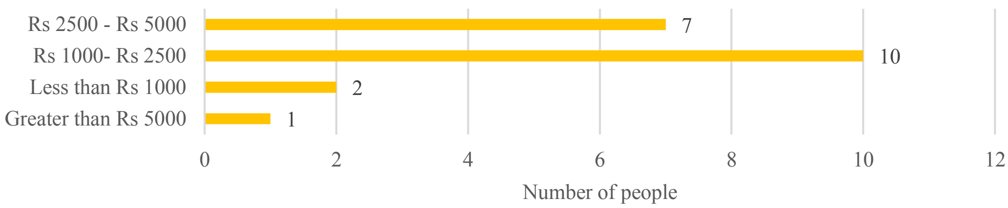

Fig.3. Survey results indicating the willingness to pay for an air quality monitoring device.

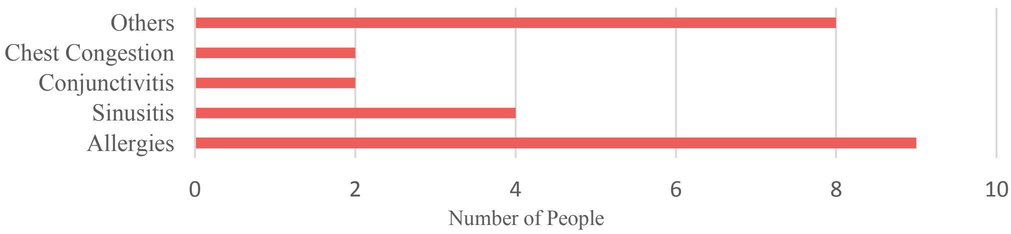

Fig.4. Survey results indicating the diseases prevalent among the Bengaluru citizens

3.2. Technical Specifications and Product Development

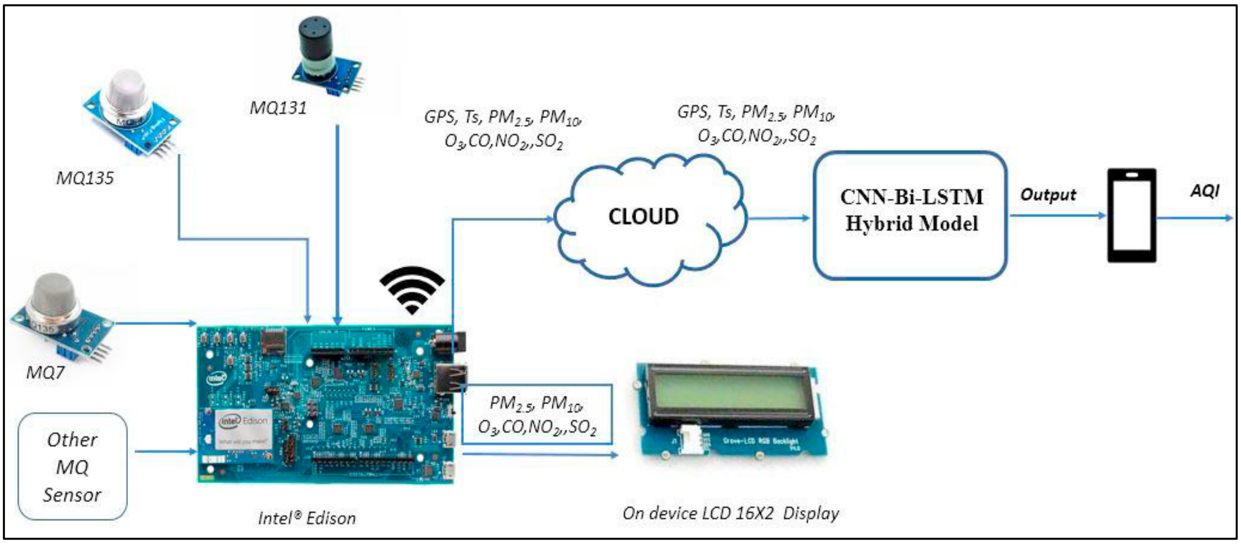

Fig 5. Circuit diagram and working of the Air Quality monitoring system AIRO.

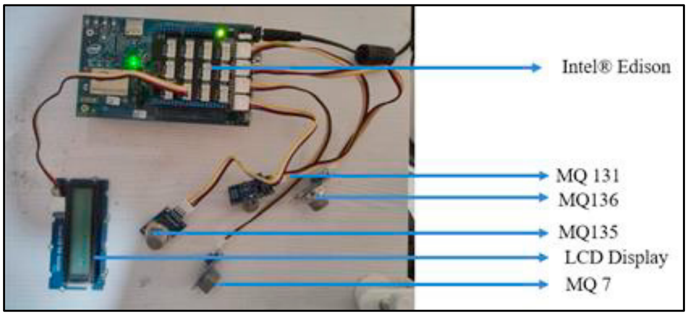

Fig. 6. Various gas sensors connected to the Intel® Edison board

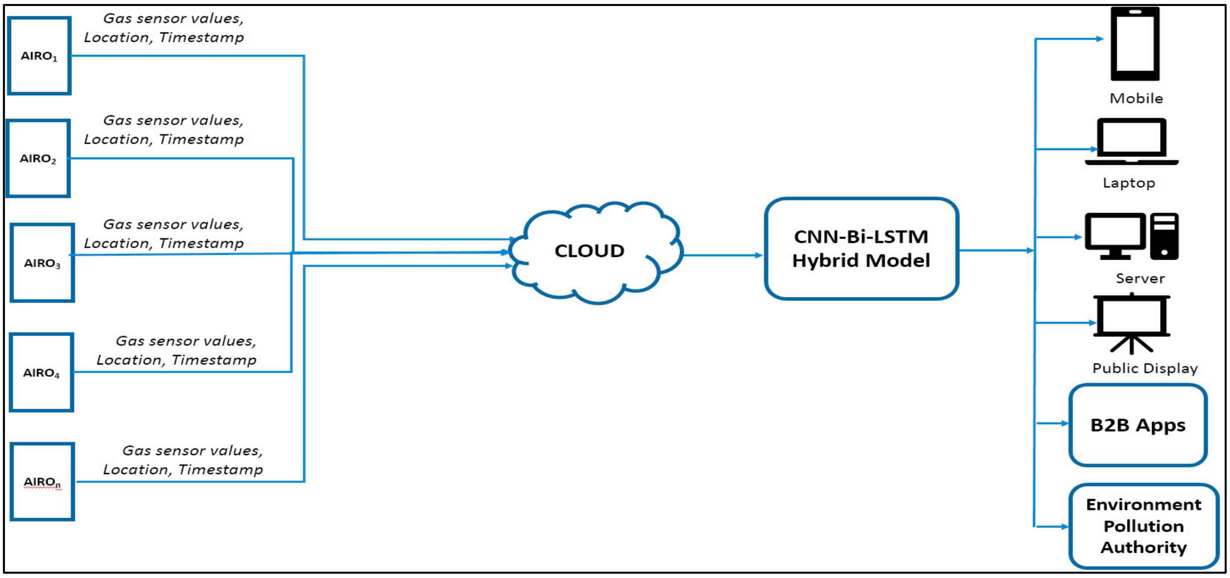

Fig. 7. System Architecture of AIRO air monitoring solution from various prototype devices at different GPS locations

AIRO, an IoT-based air quality monitoring device, is proposed to monitor the air quality in different locations in Bangalore, not just restricted to the seven centralised monitoring stations. AIRO can be easily integrated into everyday consumer products like water bottles, bags, etc., which can gather AQI data for every street in the city of Bengaluru. Each CAAQMS is highly-priced, and the setup cost may range from \$200,000, whereas an AIRO can be developed at 0.025 % of the CAAQMS cost. One of the advantages of AIRO is the possible deployment of these air quality tracking devices in every nook and corner of the city, enabling access to real-time air pollutants data to the public. The proposed framework is built on Intel® Edison with a GPS module, Wi-Fi module, MQ131, MQ135, MQ136, MQ7 sensors, and an LCD Display, as presented in **Fig. 5** and **Fig. 6**.

The prototype calculates the AQI at that location and displays it on the device-mounted LCD. These values are then sent to AWS Cloud Server, integrated with a hybrid CNN-Bi-LSTM model that forecasts the AQI daily or weekly. Python 3.10 programming language is used to read the values of the sensors and display them on the LCD. A prototype of the smartphone application is also developed to showcase the prediction of the AQI.

Initially, the Initialize( ) function ensures all the gas sensors are connected under normal conditions. The *ReadSensor( )* function collects data from all the sensors sent to the Intel® Edison for processing the AQI. The *CalculateAQI( )* function computes the AQI at that particular location. The *DisplayAQI( )* function displays the AQI value on the device's LCD screen. The *sendToCloud( )* function sends these values to the AWS cloud server, which collects data from various AIRO devices at different intervals.

The various gas sensor values collected by different AIRO devices at multiple locations are stored in the AWS cloud. **Fig. 7** presents the system architecture for the AIRO air monitoring solution deployed at various locations in the city. These compiled values are then sent as an input to the proposed CNN-Bi-LSTM hybrid Neural Network, as shown in **Fig.8**. This deep network predicts the AQI, and these values can be displayed on various projecting mechanisms like a smartphone, laptop, or public display. Custom user interfaces like smartphone apps, websites, B2B apps, etc., can take advantage of this data and develop useful applications.

3.3. Prototyping and Comparison with the existing Solutions

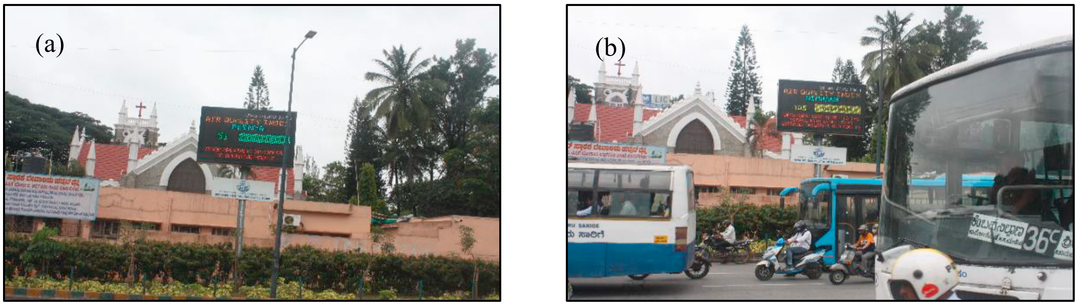

Fig. 8. (a) CAAQMS reading without traffic; (b) CAAQMS reading with traffic

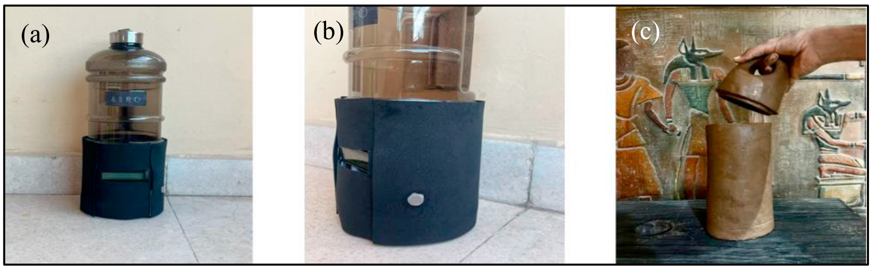

Fig. 9. (a) AIRO as a water bottle; (b) Sensors and LCD in AIRO; (c) AIRO in eco-friendly and sustainable products

As mentioned earlier, the Karnataka State Pollution Control Board (KSPCB) has set up seven Continuous Ambient Air Quality Monitoring Stations (CAAQMS) in Bengaluru. An example of CAAQMS is shown in **Fig. 8**. CAAQMS monitors PM_{10}, $PM_{2.5}$, NO_2, nitrate, etc. AIRO is a decentralised and modular solution that can be easily integrated into everyday consumer products like water bottles, bags, etc. It can gather AQI data for every street in the city of Bengaluru. **Fig. 9** presents the working prototype developed using design thinking (DT) methods from [18,19].

AIRO is portable and can be taken to any street, inside a home, or in a workplace, in contrast to CAAQMS, which are stationary. AIRO continuously senses the ambient air for pollutants, as opposed to the bulky CAAQMS, which collects a specific amount of ambient air for analysis. AIRO is cost-effective compared to the other existing models. The AIRO smartphone app gives users access to the actual and predicted air quality indices (AQI) for a specific location.

3.4. Test Data for AIRO Prototype

A house in Wilson Garden, Bengaluru, was chosen as a test case. The living room, dining room, and kitchen inside the house were selected for measurements with the AIRO prototype. A park near the home was chosen for ambient air quality measurements in Wilson Garden. Measurements were conducted inside a parked car, near the diesel inlet, and at the motorcycle and car fume outlets. The indoor air quality was then tested in the presence of volatile liquids like acetone, ethanol, and perfume. Finally, measurements were taken in Cubbon Park, a public park, and at Richmond Circle, a busy traffic intersection.

As mentioned in the earlier section, the AIRO prototype consists of 4 sensors which measure MQ135 for overall air quality, MQ2 for general combustible gas, MQ4 for methane, and MQ7 for CO. These sensors measure the concentrations in parts per million (ppm) and the results are presented in **Fig. 10**. Inside the house, it was inferred that the ‘kitchen with cooking gas on’ showed the lowest air quality over all the four gas sensors. The park in Wilson Garden and Cubbon Park has much better air quality. The air over the volatile liquids, namely, Ethanol, Acetone, and perfume, showed a higher concentration of pollutants due to volatile chemical vapours. As expected, all the vehicular gaseous emissions (car and bike) exhibited poor air quality. The air quality was moderate inside the house and the car compared to the WHO standards.

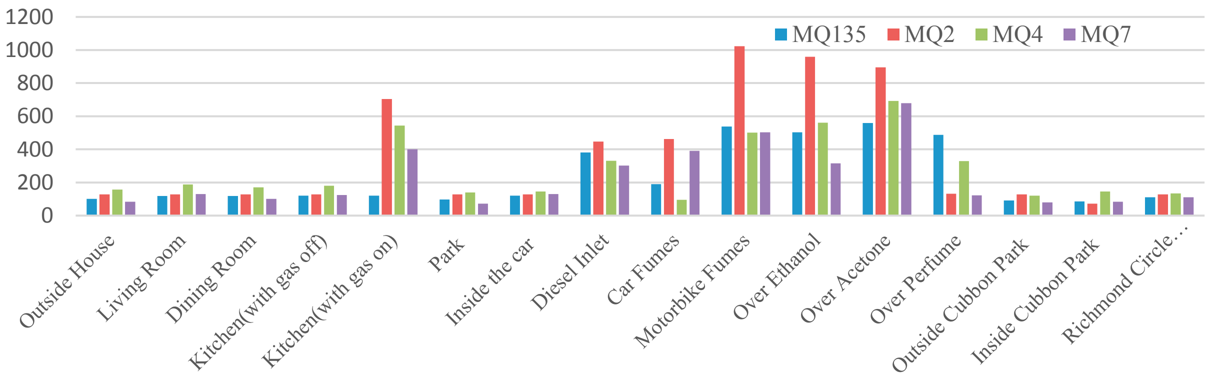

Fig .10. Gas sensor values from AIRO prototype at different locations and different scenarios

3.5. Smartphone application

Fig .11. Screens for AIRO smartphone application

AIRO smartphone app serves as a user interface (UI) for the AIRO air quality monitoring solution (AQM). The application incorporates the following functionalities – (a) provides AQI values for the current location, (b) provides AQI values based on the GPS location entered by the users, (c) provides a prediction of AQI for a particular location, and (d) indicates the other AIRO devices in the surroundings. The application screens are presented in **Fig 11**. The front end of the smartphone application was developed using Android Studio IDE, and the backend to measure the reading of various gas sensors was developed using python 3.10 programming language.

4. Discussion

AIRO is a decentralised solution that collects real-time data on various pollutants. Since AIRO is a portable solution, it can collect data from every possible street in the city. The data collected using AIRO is more realistic and diverse than from stationary point sources like CAAQMS. AIRO is an inexpensive solution compared to the existing products. AIRO contributes to the accomplishment of Sustainable Development Goals 3 (SDG 3) for good health and well-being as well as Sustainable Development Goal 13 (SDG 13) on combating climate change by promoting cleaner air and reducing air pollution.

AIRO can be integrated into a home automation system, and depending on the AQI values, a variety of actions, including turning on the air purifier, increasing the ventilation airflow, and reducing the use of gasoline-powered equipment. The data generated from AIRO can also be utilised by Pollution Control Board and notify the users of poor air quality. The citizens can take several steps to reduce air pollution, including carpooling, using public transportation, biking, or walking whenever possible. Mini air purifiers and air filters for use in a car, room, etc., can be integrated with AIRO. Deploying AIRO on a city-wide scale, with data collected in multiple locations at multiple times, can generate big data for training robust neural networks and ML models.

4.1. AQI Calculation

The Air Quality Index (AQI) is a comprehensive indicator for reporting air pollution, as suggested by the US Environmental Protection Agency. The values range from 0-500. As depicted in **Table 2**, higher values indicate greater air pollution, which causes multiple health concerns. The sensor gives a concentration reading of C(R) for each pollutant. The Index I for that pollutant is given by the following **equation (1)**. After the index is calculated for each pollutant is calculated, the AQI is simply the maximum index across all contaminants.

$$I = \frac{I(h) - I(l)}{C(h) - C(l)} * \left(C(R) - C(l)\right) + I(l) \tag{1}$$

The variables are: —

C(R) is the concentration reading of each pollutant
C(l) and C(h) are low/high concentration breakpoints that contain C(R). as defined by Environment Control Board
I(l) and I(h) are the low and high index ranges associated with concentration breakpoints for C(R).

Table 2. AQI range, descriptor suggested by US Environmental Protection Agency (adapted from [20])

AQI value	Level of Concern	Description of Air Quality
400+	Severe	Severe respiratory hazards even in healthy people
301-400	Very poor	Prolonged exposure will cause respiratory sickness
201-300	Poor	Prolonged exposure causes breathing discomfort
101-200	Moderate	People with mild lung/heart ailments face breathing discomfort
51-100	Satisfactory	Minor breathing discomfort
0-50	Good	Impact is minimal

4.2. Hybrid CNN-Bi-LSTM model for AIRO

Previous studies recommend LSTM (Long Short-Term Memory) models to be superior for training and predicting time series data such as air pollutant concentrations. As presented in Fig. 12(a), the LSTM cell acts as a memory cell to store information with three gates: the input gate (i_t), the output gate (o_t), and the forget gate (f_t). The memory cell state (C_t) is the horizontal line running through the top of the LSTM cell and is a vital component of LSTM. $\tilde{C}_t$ is the new information candidate unit value, while C_{t-1} is the previous state value (representing the historical data) processed by the LSTM cell. h_t is the hidden state of the current time step, while h_{t-1} is the hidden state at the previous time step. $\bar{x}_t$ is the current time step data or input vector. U and W are the weights for the corresponding gates. '$+$' and '$*$' represents the elementwise addition and multiplication, respectively. The input gate determines the values to be updated when a new input is acquired, while the forget gate determines which data to forget. A vector of new candidate values $\tilde{C}_t$ are generated using the *tanh* function. Finally, the final state h_t is created by O_t and C_t. A standard LSTM often is incapable of handling future information; hence in this study, a bi-directional LSTM is employed to leverage future information processing. As shown in Fig. 12(b), two hidden LSTM layers are stacked to capture the hierarchical features in the time-series data. In this Bi-LSTM model, the air pollutant concentration is divided into multiple segments based on the time series and is computed separately. The LSTM formulas are given below:

$$\text{Input Gate}: \ i_t = \sigma\left(U^{(i)}\bar{x}_t + W^{(i)}h_{t-1}\right) \tag{2}$$

$$\text{Forget Gate}: \ f_t = \sigma\left(U^{(f)}\bar{x}_t + W^{(f)}h_{t-1}\right) \tag{3}$$

$$\text{Output Gate}: \ i_t = \sigma\left(U^{(o)}\bar{x}_t + W^{(o)}h_{t-1}\right) \tag{4}$$

$$\text{Process Input}: \tilde{C}_t = \tanh\left(U^{(\tilde{c})}\bar{x}_t + W^{(\tilde{c})}h_{t-1}\right) \tag{5}$$

$$\text{Cell Update}\ : \ C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{6}$$

$$\text{Output}: \ h_t = O_t * \tanh(C_t) \tag{7}$$

A convolutional neural network (CNN) is a class of feed-forward neural networks used to predict AQI from Spatio-temporal pollutant data [21]. The CNN model has a series of convolutional and pooling layers that requires the data to be entered into a vector array format [22]. A feature map is produced by a set of convolutional filters in the convolutional layer. To convolve with specific weights, the raw input is divided into small chunks [24]. Convolutional filters can be adjusted based on input parameters to produce a different set of features. The model parameters are tuned to achieve test results with the lowest error rate [23]. One-dimensional kernels that move through the various stages act as filters that learn during the training process [24]. These CNNs can process spatial data in 3D vector arrays or matrices with superior results. The deep convolutional neural network structure used in the study consists of four hidden layers. The activation function Rectified Linear Units (ReLU) is used to pass on the local weights in the network. The present data consists of various values of the pollutants along with timestamps and locations stored in a 3-dimensional $m \times n \times k$ matrix. As shown in **Fig. 12(c)**, the proposed hybrid neural network consists of a CNN network, a bi-directional LSTM layer followed by a fully connected layer, which gives output regarding the predicted AQI and individual pollutant concentrations. The CNN considers the pollutant data for multiple timesteps from AIRO devices at different locations. Thus, the CNN component considers the spatial features impacting future air pollution. The 1D vector output of multiple air pollutant data from the CNN is fed into a bi-directional LSTM layer to ascertain the temporal domain. In these Bi-LSTM layers, the corresponding concentrations are obtained using non-linear transformations, creating a memory of information. The correlation between pollution data and time series is fully understood, and the trends for pollutant concentration change are obtained for the target data, as reported in [25]. Finally, the output from the Bi-LSTM layer is fed into a 3-layered fully connected (FC) network with a dropout of 100. This FC network acts as a classifier for AQI and gives the prediction for each pollutant separately. This CNN-Bi-LSTM hybrid model is currently trained for Bengaluru but can be extended to other cities using a transfer learning approach in the future.

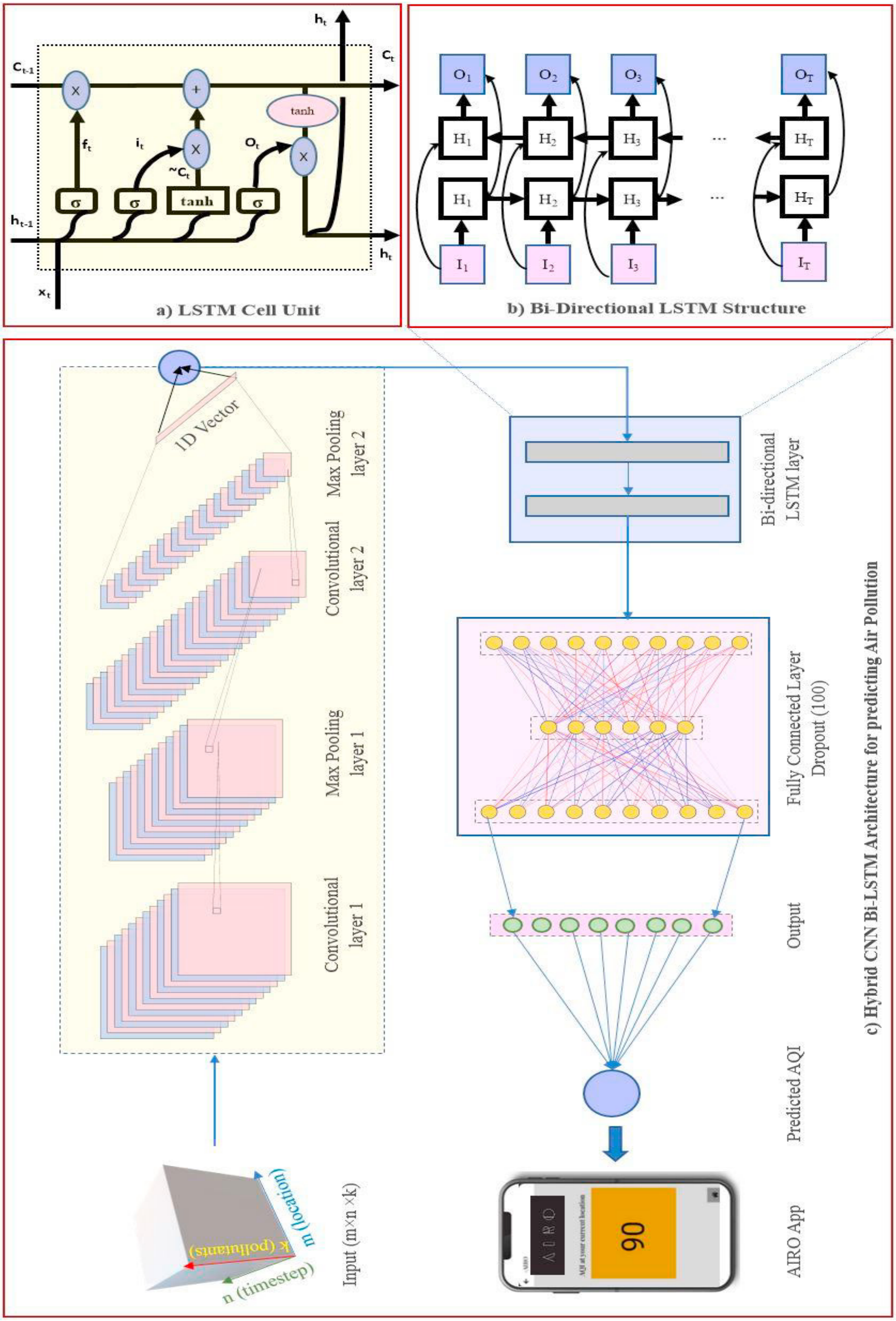

Fig .12. a) LSTM Cell; b) Bi-Directional LSTM Structure; c) Hybrid CNN Bi-LSTM Architecture for Predicting Air Pollution

4.3. Business Model

Table 3. Pricing of various components used for the AIRO framework

Components	Price (in Dollars)
Intel® Edison	$70
MQ135	$1.50
MQ131	$27
MQ136	$27
LCD Display	$4
Wi-Fi Module (esp 8266)	$1.50
AIRO Water bottle	$10
Total	**$140**

The Public-Private Partnership (PPP) between Bengaluru's startup ecosystem and the state government regulatory bodies is the foundation of AIRO's business model. AIRO can be integrated with air purification abilities to create a niche market for portable air filters and decentralised air quality monitoring solutions. The total prototyping cost of the AIRO module is $140 (**Table 3**), which can be further reduced to $45–$60 with mass-scale production efficiencies. Government environmental control boards may use the AQI values predicted by the hybrid CNN-Bi-LSTM model to alert the public to potentially dangerous AQI levels. The citizens and government entities may then take the necessary precautions to reduce the risk.

5. Conclusion

The deteriorating air quality in Bengaluru highlights the need for a decentralised air quality monitoring system that helps to understand pollutant concentrations in various parts of the city. By monitoring and regulating the real-time pollutant concentrations, respiratory illnesses brought on by air pollution could be prevented. AIRO is an IoT-based decentralised air quality monitoring solution that provides real-time AQI values. Unlike current centralised air quality monitoring systems stationed in heavy traffic intersections, AIRO is portable and built into everyday items, making it modular. AIRO is more affordable for consumers and measures the most important air-polluting gases. AIRO records the air quality indicators, calculates the AQI, and sends the data to the AWS Cloud Server. After an in-depth cloud data analysis, a hybrid CNN-Bi-LSTM model is proposed to forecast the future AQI and air pollutant concentrations. This hybrid deep-learning model can be extended to other cities using the transfer learning approach. The AIRO solution also comprises a smartphone app that helps the consumers interface with the device and easily monitor the air quality for any location. The users receive information about hazardous AQI levels in their vicinity through app notifications. AIRO helps the citizens reduce the risk of respiratory diseases by monitoring air pollution, thus promoting the SDGs of climate action (SDG 13) and good health and well-being (SDG 3).

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