Real Time Air Quality Index Monitoring and Prediction Using Lora Communication

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Abstract. This paper presents the development of a dedicated ground station optimized for LoRa satellite communication. The station is equipped with crucial components, including an antenna, transceiver, modem, RF amplifier, tracking and control system, power supply, computer with specialized software, networking infrastructure, and weatherproofing. The RF amplifier is instrumental in boosting signal strength and expanding the communication range to counteract transmission signal loss. The tracking and control system ensures precise alignment of the antenna with the satellite, ensuring a consistent and dependable connection. A reliable power supply, coupled with backup sources like batteries or generators, mitigates downtime risks. The computer system, integrated with specialized software, manages transceiver setup, satellite tracking, and data processing. Networking equipment facilitates internet or local net-work connectivity for seamless data exchange and remote monitoring. Weather proofing measures are implemented to safeguard the station's equipment. This comprehensive ground station design is geared towards enhancing the efficiency and reliability of LoRa satellite communication, delivering tangible benefits to researchers, engineers, and IoT practitioners.

Keywords: LoRa technology · antenna · transceiver · Ground station · Networking · equipment

1 Introduction

Our atmosphere's quality has become a critical concern in an era marked by growing urbanization and industry. In addition to being a fundamental human right, having access to clean, breathable air is essential to the health of our world. A remarkable collaboration between wireless communication technologies and space technology has evolved to address this problem: LoRa (Long Range) communication-equipped Cube Sat. The goal of this paper is to investigate the creative fusion of LoRa communication networks and CubeSat technology for the evaluation and distribution of vital air quality data. Small satellites called Cube Sat, which have dimensions of 10 x 10 x 10 centimeters [1], provide a flexible platform for data collecting and remote sensing while in Earth's

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orbit. The monitoring of the environment, especially air quality, could be revolutionized by these reasonably priced tiny satellites. With an ambitious and broad scope, the paper will create a CubeSat fitted with state-of-the-art air quality sensors. These sensors gather data in real-time on several atmospheric characteristics, such as nitrogen dioxide (NO2), carbon monoxide (CO), and particulate matter (PM2.5 and PM10).

Applications like policy development, public health management, environmental research, and urban planning could benefit from the precise measurement and return of this data to Earth [2]. This paper's use of LoRa communication technology is essential. LoRa is appropriate for difficult and distant situations since it allows Cube Sat to transmit data to ground stations efficiently. The technical details of LoRa communication protocols, sensor integration and CubeSat design, as well as the creation of a strong ground station network for data receipt and analysis, will all be covered in this paper. It will also examine the possible advantages and difficulties of this novel strategy for monitoring air quality. In conclusion, air quality monitoring could undergo air evolution because of the combination of LoRa communication with CubeSat technology [3]. Our goal as we work on this paper is to uncover the possibility of a sophisticated, affordable method for assessing the quality of the air worldwide. The data gathered by this cutting-edge system has the potential to improve public health, spur positive change, and pave the way for a sustainable, ecologically conscious future. This paper is a major step in our continuous effort to solve the problems caused by environmental degradation and air pollution. Radio waves are essential for satellite communication with Earth's ground stations. They use transponders and antennas to receive and send signals. It will also examine the possible advantages and difficulties of this novel strategy for monitoring air quality.

In conclusion, air quality monitoring could undergo a revolution because of the combination of LoRa communication with CubeSat technology [4]. Our goal as we work on this paper is to uncover the possibility of a sophisticated, affordable method for assessing the quality of the air worldwide. The data gathered by this cutting-edge system has the potential to improve public health, spur positive change, and pave the way for a sustainable, ecologically conscious future. This paper is a major step in our continuous effort to solve the problems caused by environmental degradation and air pollution. Radio waves are essential for satellite communication with Earth's ground stations. They use transponders and antennas to receive and send signals (see Fig. 1).

2 Related Work

In recent years, there has been a growing interest in employing advanced technologies to address air quality monitoring and prediction challenges. This section presents are view of relevant literature in this domain. Noreen et al. (2017) [5] evaluated the effectiveness of cutting-edge hybrid deep learning techniques for air quality prediction, considering the influence of meteorological parameters. Their study contributes to understanding the potential of hybrid deep learning approaches in improving air quality prediction accuracy. Yuliarto et al. (2015) [6] proposed a real-time air quality monitoring and prediction system tailored for urban areas. Their work encompasses the entire development process of an end-to-end AQI monitoring system, including deployment considerations specific to urban environments.

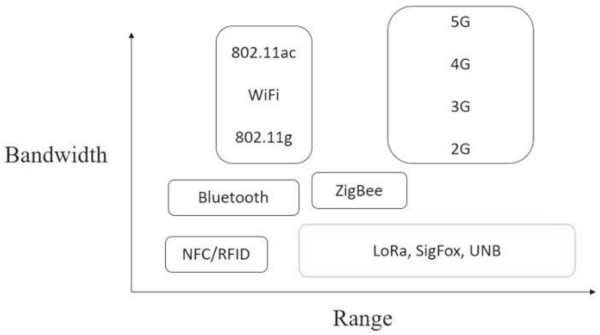


Fig. 1. Lora Bandwidth range compared with frequency.

The integration of satellite data for air quality monitoring is explored in the study titled “FEMTOSAT-Based Air Quality Monitoring” by Horn et al (2019) [7]. This research investigates the integration of satellite data and LoRa communication to enhance AQI pre-diction accuracy, highlighting the potential of remote sensing technologies. In the realm of sensor technology, Kanchan et al. (2023) conducted a study on SnO2nanostructures as pollutant gas sensors. Their research provides insights into the synthesis, sensing performances, and mechanisms of SnO2-based gas sensors, which are crucial for developing efficient air quality monitoring systems [8]. Furthermore, the utilization of LoRa technology for air quality monitoring has garnered significant the capabilities of LoRa low-power wide-area network technology [9], while Vicente et al. (2016) investigated its adaptability in the context of LEO satellites Internet of Things (IoT) [10]. In terms of infrastructure and standards, Carlson and Rysgaard (2018) explored the adaptation of open-source drone autopilots for real-time iceberg observations, which could have implications for environmental monitoring applications. Additionally, Devalal et al. the General Environmental Verification Standard (GEVS) by NASA Goddard Space Flight Center provides a framework for ensuring the quality and reliability of environmental monitoring systems [11].

The rise of small satellite technologies is evident in ESA’s CubeSat initiative (2018),which offers opportunities for innovative approaches to environmental monitoring, including air quality assessment [12].Finally, various resources such as the Air Quality Index (AQI) basics provided by the United States Environmental Protection Agency(EPA) and Air Now offer foundational knowledge, while industry initiatives like the LoRa Alliance and practical implementations documented by Hackster.io contribute to the dissemination and advancement of air quality monitoring solutions. The review by Od et al. underscores the diverse array of approaches and technologies being employed to address air quality monitoring challenges, ranging from advanced data analytics to innovative sensor platforms and satellite-based solutions [13].

3 Problem Identification

The traditional approach of employing stationary sensors on buildings has drawbacks due to growing worries about air quality and its effects on respiratory health, especially in isolated locations with few structures. Innovative solutions to this problem measure pollutants including PM10, PM2.5, NO2, and more using Cube Sat, tiny spacecraft with a variety of sensors. A complete air quality monitoring system is created by combining data from satellites like NOAA's GOES-R and JPSS with data from ground sensors and Cube Sat. These satellites offer global-scale, real-time observations of carbon monoxide, ozone, and particulate pollution. Researchers may better understand Earth's intricate relationships by using this data into sophisticated computational models, which helps with environmental predictions for wise policy and public health management. By using machine learning models and cloud computing to forecast Air Quality Index levels, the proposed paper seeks to construct a CubeSat with integrated sensors for autonomous air pollution monitoring.

4 Implementation

The integrated sensors, OBC, LoRa Tx transmitter, and Microcontroller are all connected inside the Cubesat. (IOT embedded system) The Node MCU ESP8266 is a wifi module. It is connected to the LoRa receiver Rx. Data processing is done using programming within the Node MCU, resulting in the digital representation of the data. The information kept on the AWS cloud will be handled and transformed into the necessary file format. It is necessary for the data to be in CSV file format. This will also be utilized as a Dataset for training and forecasting the amount of air pollution, or AQI level, in different areas. This dataset will be used as a training set for models in the future. After Cube satellite is launched in e-LEO, the data may be seen on-site using a portable ground station. It can also be displayed, analyzed, and tracked via Thing Speak Server. Cloud-based data stream collection, visualization, and real-time analysis are made easier with Thing Speak, an IoT Analytics solution (see Fig. 2).

Devices send data to Thing Speak, which displays it quickly. Use the Thing Talk IoT application and API, which are available for free, to save and retrieve data via HTTP via a local area network or the Internet. Global remote data viewing is made possible by this technology. To determine the Air Quality Index (AQI), you must submit data for a minimum of three pollutants, such as PM2.5 or PM10. In order to determine the Air Quality Index (AQI), you must submit data for a minimum of three pollutants, such as PM2.5 or PM10. Every pollutant has a different concentration and associated health impact along the AQI's 0–500 range.

5 Machine Learning Approach

Machine learning (ML) is a computational approach enhancing knowledge acquisition from experiences, enabling machines to learn and respond intelligently. It proves particularly valuable in forecasting tasks, such as predicting air quality data, where linear models may fall short. Our focus is on accurately predicting harmful gas levels (O3,

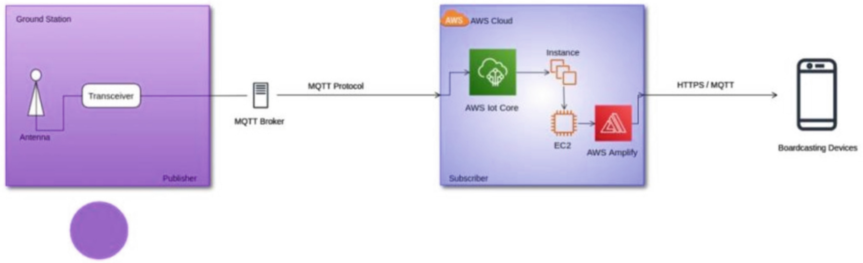


Fig. 2. Architecture Diagram of Workflow for Integrating Air Quality Sensors with the Server

NO2, SO2) using nonlinear modeling techniques. We employ the Brocke-Decherte-Scheinkman (BDS) method as given in Eqn.1 to confirm nonlinear patterns in the data. The BDS statistic, ω_m, n(ε),

$$\omega_{m,n}(\varepsilon) = \sqrt{n}\frac{c_{m,n}(\varepsilon) - c_{1,n}^{m}(\varepsilon)}{\sigma_{m,n}(\varepsilon)} \quad (1)$$

The notation includes "n" for sample size and "m" for embedding dimension, typically ranging from 2 to 5 for larger sample sizes. "σ" signifies time series standard deviation, and "ε" is recommended between 0.5σ and 2σ for normally distributed samples. Calculated ωm, n(ε)values for SO2, NO2 and O3 fall within [207.36–266.12], [140.72–176.42], and [191.43–224.35] ranges, respectively. These values significantly surpass the 1.96 threshold, robustly confirming the evident nonlinearity in the data, assuming a normal or near-normal distribution.

Our process includes the following crucial phases (see Fig. 3). In data preprocessing, meticulous cleaning removes anomalies for optimal compatibility with machine learning. Feature engineering selects pertinent attributes like humidity and temperature. Time series forecasting uses time windowing, creating time-lagged features to highlight temporal relationships. Building models involves training on historical data, gathering known target values, and validating through testing with various sliding windows. Performance metrics like RMSE (Eq.2) and Prediction Trend Accuracy (PTA) assess model robustness. PTA evaluates alignment between actual and predicted trends, crucial for public health and environmental decisions. Formulas use "Label" for air quality measurements and "horizon" for future steps, assessing trend alignment by multiplying trends and dividing by occurrences.

$$\mathrm{RMSE} = \sqrt{}(\Sigma(\mathrm{y} - \overline{\mathrm{y}})2/\mathrm{n}) \quad (2)$$

where "n" denotes the number of instances, "y" is the actual value of the target feature, and "$\overline{\mathrm{y}}$" represents the predicted value of the target feature. To enable a fair comparison of model performance across different models predicting various target variables, as per Eq. 3 Normalized RMSE (NRMSE) is utilized. NRMSE is calculated as:

$$\mathrm{NRMSE} = \mathrm{RMSE}/\left(\mathrm{y}_{\max} - \mathrm{y}_{\min}\right) \quad (3)$$

In air quality prediction, Root Mean Square Error (RMSE) and Normalized RMSE (NRMSE) are pivotal metrics for assessing forecasting model accuracy. RMSE quantifies overall prediction error by comparing actual and predicted values, while NRMSE

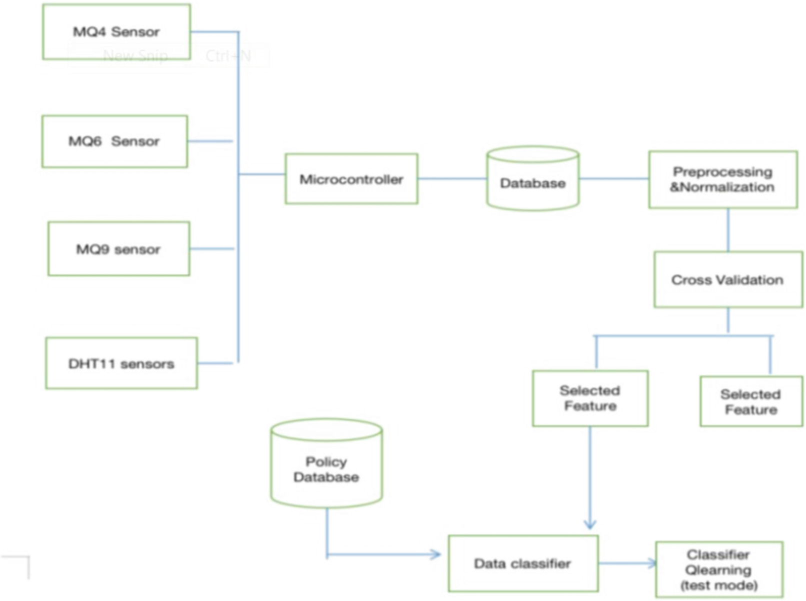


Fig.3. Flow diagram of data flow in the machine learning approach

normalizes RMSE, facilitating fair model comparisons across various parameters. Both metrics play a vital role in validating and ensuring the accuracy of air quality forecasting models, crucial for informed decisions in public health and environmental management. In the deployment phase, unseen data is processed using the best model, with continuous performance monitoring and iterative training, testing, and deployment for result accuracy, especially in dynamic environments. Support Vector Machine (SVM), Artificial Neural Networks (ANN), and M5P are effective algorithms for constructing these forecasting models, each offering distinct advantages based on input data characteristics (see Fig4)

6 System and Architecture Design

The utilization of CubeSat-based systems to monitor air quality represents an innovative approach in tackling the escalating concerns linked to air pollution. Cube Sat, characterized by their standardized cube-shaped design, provides cost-efficient and adaptable platform for gathering crucial environmental information. The design and structure of the system for air quality monitoring using Cube Sat encompasses several pivotal components (see Fig. 5).

The choice of CubeSat size (1U, 2U, or 3U) depends on mission requirements and payload capacity. Larger Cube Sat offers increased sensor accommodation, enhancing data collection capabilities. Cube Sat feature sensors for monitoring air quality parameters (PM, NO2, CO2) and meteorological data (temperature, humidity, pressure).Sensor selection considers factors like power consumption, size, weight, and accuracy. Cube Sat

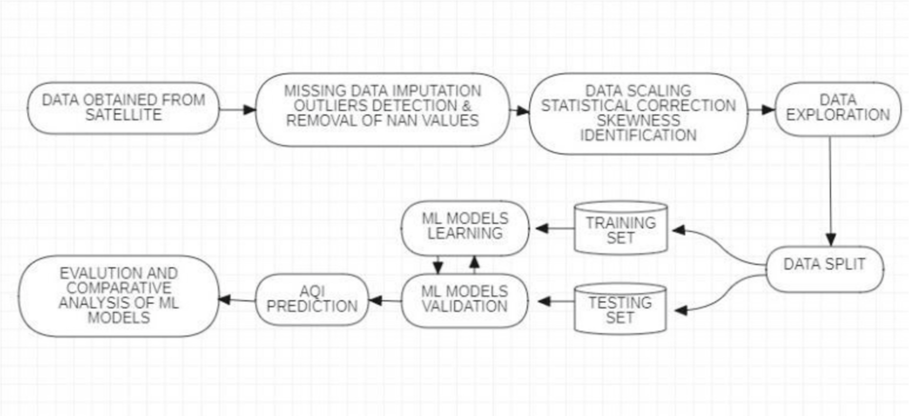


Fig. 4. Iterative Process of constructing and applying ML-based prediction models

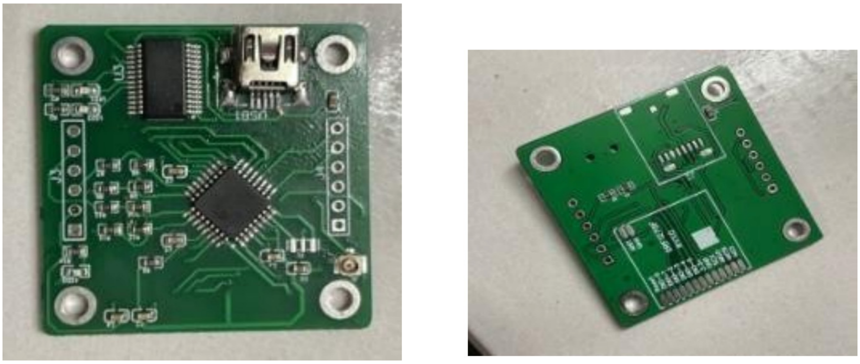


Fig. 5. Hardware part of On-board computer design

includes onboard data processing units for sensor data analysis and initial data reduction, reducing data transmission requirements and conserving power. Low Earth Orbit (LEO) communication systems, utilizing technologies like LoRa, UHF, or Sband, establish reliable data links for transmitting collected data to ground stations [see Fig. 6].

Cube Sat function within Low Earth Orbit (LEO), and strategically positioned ground stations are responsible for receiving and processing data. These stations facilitate both data downlink and uplink, tracking the satellite as it orbits. To generate electrical power, Cube Sat commonly employs solar panels. Excess energy is stored in energy storage systems, typically in the form of batteries. This stored energy becomes invaluable during eclipses when the satellite finds itself in Earth's shadow. To maintain the CubeSat's internal components within the designated temperature ranges Amidst the challenging conditions of space, effective thermal control mechanisms are implemented. These mechanisms encompass both passive and active systems [see Fig.7].

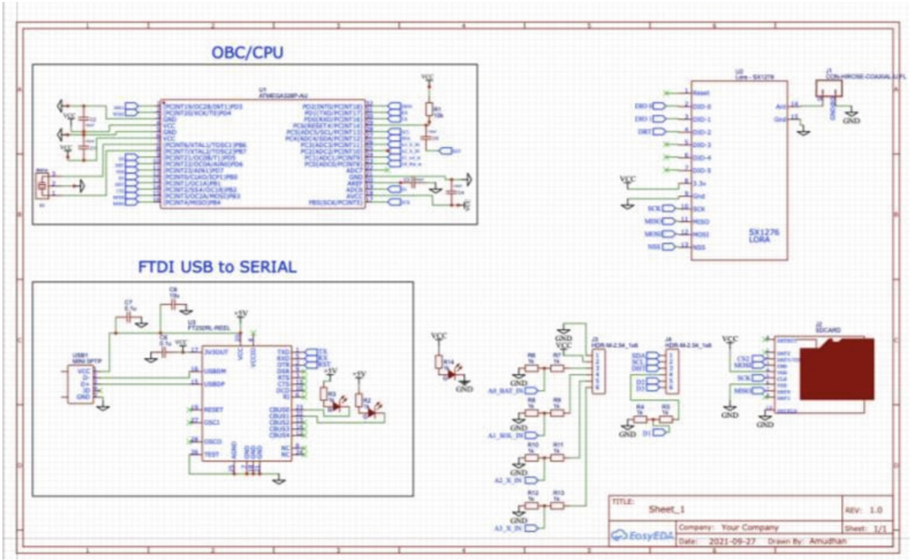


Fig. 6. Systematic design of on-board computer

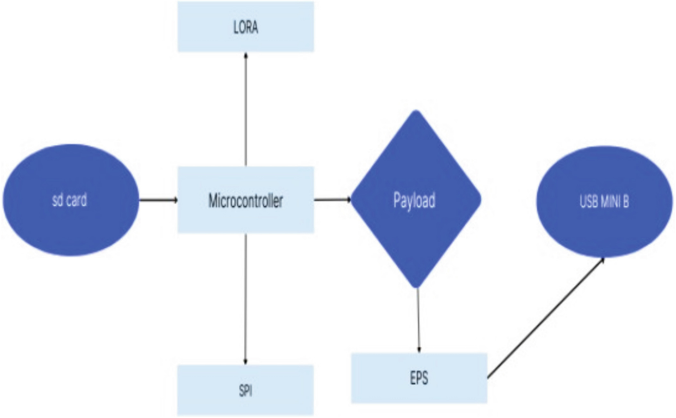
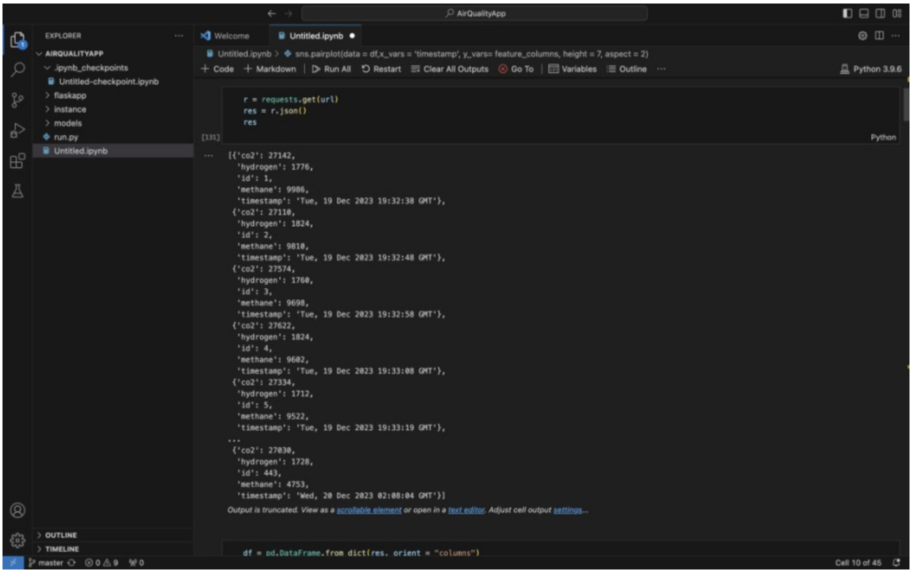


Fig. 7. Block diagram of CubeSat workflow

Cube Sat necessitates precise attitude control systems for satellite orientation, directing sensors, and optimizing solar panel power generation. Onboard data storage is crucial for temporarily housing collected data, while telemetry systems provide real-time updates on satellite health. Ground-based processing transforms CubeSat data into air quality indices, utilizing machine learning for enhanced analysis. Software onboard and on the ground supports data processing, sensor calibration, and predictive modeling. Mission planning involves defining orbits, data collection schedules, and communication strategies, with continuous monitoring by operations teams. Safety proto-cols prevent satellite risks, and contingency plans address emergencies. CubeSat-collected air quality data is shared openly, accessible via user-friendly platforms, fostering collaboration between satellite technology, environmental science, and data analytics experts. This collaborative system design offers an innovative approach to addressing global air quality concerns, informing environmental policies and public health initiatives as Cube Sat technology advances.

7 Results and Discussion

In this paper, the Arduino IDE was leveraged to implement and test the functionality of MQ135 and MQ7 sensors. The real-time output from these sensors was systematically monitored in the serial monitor, accompanied by timestamps, establishing a robust foundation for continuous data acquisition. Furthermore, the implementation of the Thing speak server (see Fig. 8) served as a pivotal component, enabling internet-based delivery of gas percentage measurements. This setup allows for seamless remote monitoring worldwide, even during travel. Additionally, for the anticipation of pollutant and particulate levels, along with the prediction of the Air Quality Index(AQI), various machine learning algorithms, including Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), Random Forest (RF), and Logistic Regression, were employed (see Fig. 9)). This comprehensive approach significantly enhances the precision and reliability of AQI predictions, marking a significant advancement in air quality forecasting methodologies [see Fig. 10].



```
r = requests.get(url)
res = r.json()
res
```

```
[{'co2': 27142,
  'hydrogen': 1776,
  'id': 1,
  'methane': 9986,
  'timestamp': 'Tue, 19 Dec 2023 19:32:38 GMT'},
 {'co2': 27110,
  'hydrogen': 1824,
  'id': 2,
  'methane': 9810,
  'timestamp': 'Tue, 19 Dec 2023 19:32:48 GMT'},
 {'co2': 27574,
  'hydrogen': 1760,
  'id': 3,
  'methane': 9698,
  'timestamp': 'Tue, 19 Dec 2023 19:32:58 GMT'},
 {'co2': 27622,
  'hydrogen': 1824,
  'id': 4,
  'methane': 9602,
  'timestamp': 'Tue, 19 Dec 2023 19:33:08 GMT'},
 {'co2': 27334,
  'hydrogen': 1712,
  'id': 5,
  'methane': 9522,
  'timestamp': 'Tue, 19 Dec 2023 19:33:19 GMT'},
...
 {'co2': 27030,
  'hydrogen': 1728,
  'id': 443,
  'methane': 4753,
  'timestamp': 'Wed, 20 Dec 2023 02:08:04 GMT'}]
```

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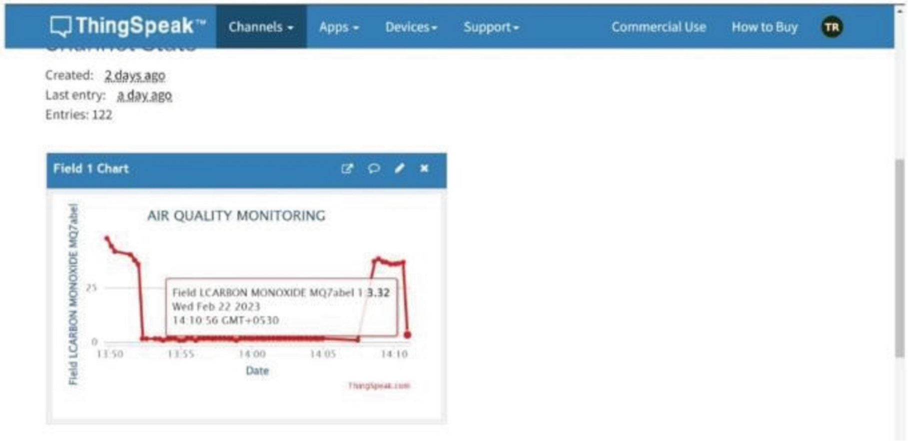
```
df = pd.DataFrame.from_dict(res, orient = "columns")
```

Fig. 8. In the Visual studio, MQ135 and MQ7 sensors are implemented to test their functionality, with the output monitored in the serial monitor along with timestamps.



Created: 2 days ago
Last entry: a day ago
Entries: 122

Field LCARBON MONOXIDE MQ7abel 1: 3.32
Wed Feb 22 2023
14:10:56 GMT+0530

Fig. 9. The Thing speak server facilitates internet-based delivery of gas percentage measurements, allowing remote monitoring worldwide, even while traveling.

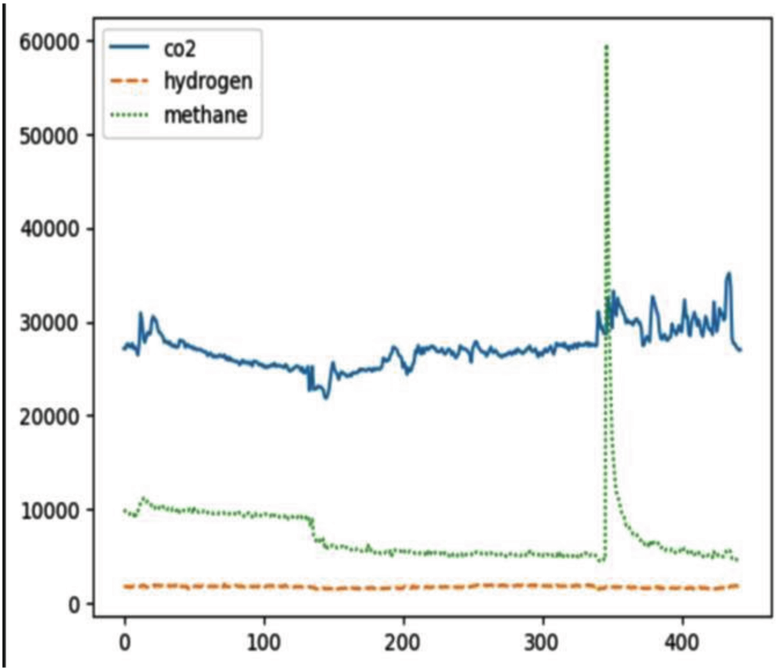


Fig. 10. To forecast pollutant and particulate levels along with predicting the AQI, various machine learning algorithms such as Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), Random Forest (RF), and Logistic Regression are employed.

8 Conclusion

The development of air quality prediction is a major advancement in the fight to safeguard the environment and human health. Accurately predicting air quality indicators has become crucial in tackling the problems caused by air pollution in an era of fast industrialization and urbanization. With the use of sophisticated data analytics and environmental monitoring, air quality prediction models provide vital information about pollutant concentrations and possible outcomes. These paper ions provide the information required for governments, environmental organizations, and the public to make educated decisions, carry out pollution management strategies, and protect communities that are particularly vulnerable. Air quality prediction is no longer only a scientific endeavor in our increasingly complex and linked world; it is now an essential part of public health and sustainability of the environment. We can reduce pollution, address air quality problems proactively, and improve the lives of current and future generations by utilizing technology and data. The continuous search for cleaner air is made possible by air quality forecast, which is an essential source of guidance.

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