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IoT-Based Air Quality Monitoring and Prediction System

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Abstract

Air pollution is a major environmental issue affecting public health and urban sustainability. Traditional air quality monitoring systems are costly, have limited coverage, and lack predictive capabilities. This paper proposes an IoT-enabled Air Quality Monitoring and Predicting System consisting of MQ-series gas sensors, Raspberry Pi, Random Forest machine learning algorithm, and cloud computing for real-time monitoring and AQI prediction.

The system uses MQ-2, MQ-4, MQ-7, MQ-9, and MQ-135 sensors in conjunction with a DHT-11 temperature and humidity sensor, connected to a Raspberry Pi via an MCP3208 ADC. The sensor data is processed using the Random Forest algorithm to provide predictions for AQI. The data is streamed over the ThingSpeak IoT cloud, graphed, and made accessible via a mobile application. Users receive real-time alerts when air quality is poor.

Outcomes show that the system gives a sensor accuracy of 92-95 percent and AQI forecast accuracy of 85-90 percent. The cloud-to-mobile latency is approximately three seconds, which means almost instantaneous updates. Compared to conventional monitoring mediums, the system is cost-effective, scalable, efficient, and suitable for use in smart cities and industries.

The study concludes that the convergence of IoT, machine learning, and cloud computing makes real-time air quality monitoring and forecasting possible. Some future enhancements include deep learning, edge AI, and increased sensor coverage.

Keywords: Air Quality Monitoring, IoT, Machine Learning, Random Forest, Raspberry Pi, AQI Prediction, Cloud Computing.

1. Introduction

Air pollution is presently one of the most detestable environmental and health hazards of the contemporary world. Industrial emissions, motor vehicle exhaust gases, and deforestation account for the largest share of the increasing air pollutant levels like carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter (PM2.5, PM10). The long-term effects of the aforementioned air pollutants cause respiratory illness, cardiovascular ailments, lung cancer, and diminished life expectancy. To counteract such risks, there have to be effective air quality forecasting and monitoring systems.

The traditional departmental-operated air quality monitoring stations are stationary, expensive, and have a restricted coverage area. The stations simply capture available data but do not have predictive features. Further, the data provided by them are mostly not downloadable by the masses, thus people are unable to take preventive action. To steer clear of such limitations, this study suggests an IoT-based Air Quality Monitoring and Forecasting System with real-time data collection, processing, and forecasting through the help of machine learning techniques.

The suggested system is designed with Raspberry Pi as the main processing unit and coupled with MQ-series gas sensors (MQ2, MQ4, MQ7, MQ135, and MQ9) to detect different toxic gases, such as carbon monoxide, methane, and ammonia. Besides that, a DHT-11 sensor is utilized to determine the humidity and temperature since environmental weather outside also has an impact on the air quality. The data collected is analyzed and processed with the assistance of a Random Forest Machine Learning model to predict the Air Quality Index (AQI) and air quality categorization into various safety zones (Good, Moderate, Unhealthy, and Hazardous).

The system is also supplemented with cloud integration, where ThingSpeak IoT Cloud is used to store, visualize, and analyze air quality data in the long term. There is a mobile application, created using MIT App Inventor, that allows users to monitor current air pollution levels remotely and receive alerts whenever air quality goes beyond safe levels. The mobile application has simple-to-use graphical representations, which allow simple monitoring of pollution trends and preventive measures.

The key project objectives are:

1. **Develop a real-time air quality monitoring system** using IoT sensors and Raspberry Pi.
2. **Predict AQI using a machine learning model (Random Forest Algorithm)** to provide early warnings.
3. **Enable remote monitoring** through a mobile application and ThingSpeak cloud platform.
4. **Improve system accuracy** and optimize data collection for better environmental decision-making.
5. **Enhance public awareness** by providing accessible, real-time pollution data.

The purpose of this study is to create an affordable, portable, and expandable technology that can be applied in homes, industry, schools, and cities. The convergence of IoT, cloud computing, and machine learning offers an efficient, automated, and predictive air quality monitoring system that ensures enhanced environmental management and public health security.

2. Literature Review

Advancements in Internet of Things (IoT) and Machine Learning (ML) have significantly enhanced the ability of air quality monitoring through real-time collection, analysis, and forecasting. Conventional government-run sensor networks have been utilized in current air quality monitoring systems that are expensive and non-scalable. IoT-based systems provide a viable alternative through the utilization of low-cost sensors, cloud computing, and smart algorithms for providing accurate and real-time air pollution evaluation. Various research papers have discussed IoT and ML integration for air quality monitoring, resulting in innovative solutions for real-time data collection, predictive analytics, and mobility.

Barot and Kapadia [1] analyzed and reviewed IoT-based air quality monitoring systems thoroughly and identified issues with data accuracy, sensor calibration, and predictive analysis. The study highlighted the importance of machine learning models to improve the accuracy of IoT sensors and air quality prediction.

Karnati [2] also proposed an IoT-ML hybrid model that uses sensor data analytics to predict pollution levels accurately. The study demonstrated that Random Forest and XGBoost are ML algorithms that significantly enhance AQI prediction over baseline statistical models.

Kaur and Sharma [3] explained some of the IoT-based air quality monitoring systems and the major components as gas sensors, cloud integration, and mobile applications. Kaur and Sharma have categorized air quality monitoring technologies into fixed station-based monitoring and portable sensor-based monitoring. Fixed stations provide high accuracy but with restricted coverage, whereas portable sensor-based solutions provide scalability and real-time monitoring. The accuracy of portable sensors is still a problem due to environmental influences.

Kumar, Kumari, and Gupta [4] designed an IoT-based system for air quality monitoring with integration in ThingSpeak Cloud for visualizing data. Their work dealt with using cloud computing for data storage and retrieval of real-time data. L [5] extended that considering the impact of sensor position and calibration on the accuracy of the data. From the study, it was established that IoT sensors must be calibrated from time to time in order to provide consistency to AQI reading.

Munera et al. [6] had performed a systematic mapping of smart city air quality monitoring systems. Sensor data fusion and real-time analytics play a major role in improving pollution detection, as found by them. The research found that edge computing enhances real-time decision-making through processing the data at the source and minimizing dependency on the cloud.

Machine learning has been used as a consistent aid in air quality level prediction and to enhance the predictive accuracy of IoT-based systems. N, N. H. G., R, N. A., and R, N. N. [7] explored ML-based methods towards analysis of air pollution data. Through their research, they realized that Random Forest, XGBoost, and Deep Learning models were more predictive efficient than the conventional methods. The research identified feature selection as a door opener to better AQI forecasts.

Pemula et al. [8] proposed an artificial intelligence-enabled IoT-air pollution forecasting system. Authors have proved through their research that using machine learning with IoT data provides adaptive pollution warning and forecasting. Likewise, Pendekanti et al. [9] investigated current advances in IoT-air quality monitoring and control and laid focus on the need for predictive modeling in avoiding exposure to pollution.

Tan et al. [10] performed an extensive survey of indoor air quality monitoring through IoT and concluded that sensor networks, AI-driven analytics, and real-time alert significantly enhance environmental monitoring. They identified data security and scalability as major challenges in IoT deployments.

Research Gaps and Challenges

Despite the advancements in **IoT and ML-based air quality monitoring**, several **research gaps** remain:

1. **Sensor Calibration & Data Accuracy:** IoT-based systems are generally missing consistency in their data due to sensor drift and environmental factors [1][5].
2. **Real-Time AQI Prediction Limitations:** Current systems revolve around real-time monitoring in place of heavily resilient predictive strength [2][7].
3. **Cloud Dependency & Latency Issues:** Some systems use cloud processing, adding latency while interacting with real-time data [6].
4. **User Accessibility & Mobile Alerts:** Though some research considers mobile integration, real-time user notifications are sparse [3][8].

Bridging the Research Gaps

To address these limitations, our research **proposes an IoT-driven air quality monitoring system** that integrates:

1. **Real-Time AQI Prediction:** Using a Random Forest Machine Learning algorithm to predict air pollution levels better than statistical methods.
2. **Enhanced Sensor Calibration:** Using adaptive calibration methods to enhance sensor accuracy and minimize data differences.
3. **Low-Latency Data Processing:** Using ThingSpeak Cloud and Edge AI to support real-time decision-making with minimal latency.
4. **Mobile Accessibility & Alerts:** Designing a mobile app with recent air pollution data and real-time alerts to create user awareness and engagement.

Utilizing the cooperation of IoT, cloud computing, and machine learning, our approach offers a low-cost, expandable, and predictive air quality monitoring solution improving public health safety and environmental conscience.

3. Methodology

This sub-section discusses the system design, development, and functionality of the IoT-based air quality monitoring and forecasting system. The system includes hardware elements (sensor, Raspberry Pi, ADC, LCD display, buzzer), software (Python, ThingSpeak, mobile application), and a Machine Learning algorithm (Random Forest) to forecast AQI.

3.1 System Architecture

The system is based on the multi-layered system which utilizes sensor networks, processing nodes, cloud storage, and mobile communication in a bid to sense and forecast air quality in real-time.

Block Diagram of the System

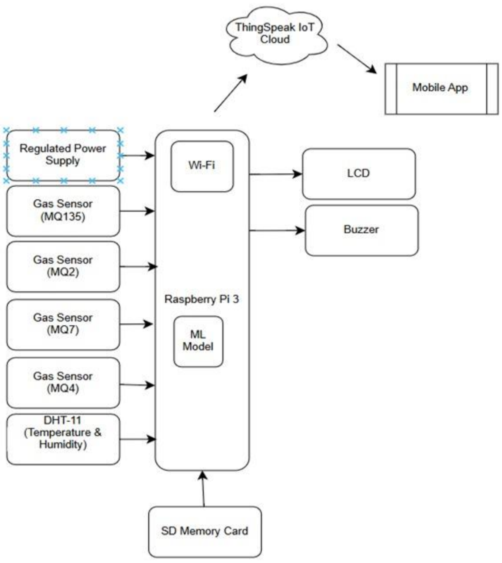

Figure 3.1: System Block Diagram

The system consists of:

1. **Sensing Layer:** IoT sensors (MQ2, MQ4, MQ7, MQ135, MQ9, DHT-11) collect real-time air pollution data.

2. **Processing Layer:** Raspberry Pi processes sensor data, applies **ADC conversion**, and runs the **Random Forest ML model** for AQI prediction.
3. **Cloud Layer:** ThingSpeak IoT platform stores, processes, and visualizes data.
4. **Application Layer:** A mobile app displays real-time AQI values and **sends alerts if pollution exceeds safe levels**.

3.2 Hardware Components

The system is built using **cost-effective IoT sensors and microcontrollers** for efficient air quality monitoring.

3.2.1 Raspberry Pi 3

- Acts as the **central processing unit** of the system.

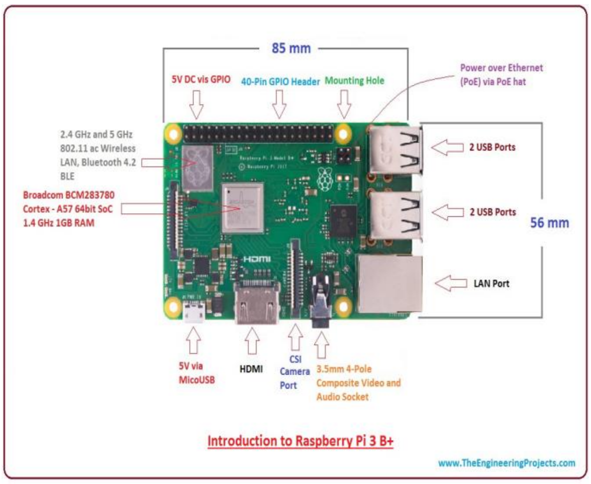

Figure 3.2: Raspberry Pi 3B+ Board Layout

- Reads sensor values via **GPIO pins**.
- Runs the **Random Forest ML model** to predict AQI.
- Transmits data to the **ThingSpeak cloud** and mobile app.

3.2.2 Gas Sensors (MQ Series)

These sensors detect **various harmful pollutants** and send data to Raspberry Pi for processing.

Sensor	Detected Pollutants
MQ-2	LPG, Methane, Smoke
MQ-4	Natural Gas, Methane
MQ-7	Carbon Monoxide (CO)
MQ-9	CO, Methane, LPG
MQ-135	NH3, Benzene, NO_2, Smoke

- **Analog output converted to digital** using MCP3208 ADC.

Figure 3.3: MQ-Series Gas Sensor

- Used to **calculate AQI levels** and trigger alerts.

3.2.3 DHT-11 Sensor (Temperature & Humidity Monitoring)

- Measures **temperature and humidity** (factors affecting AQI).
- Helps in **sensor calibration** to improve accuracy.

3.2.4 MCP3208 Analog-to-Digital Converter (ADC)

- Converts **analog sensor signals to digital format** for Raspberry Pi processing.
- **12-bit resolution** ensures **higher accuracy** in pollutant measurement.

3.2.5 LCD Display & Buzzer

- **LCD Screen (16x2)**: Displays real-time AQI levels.

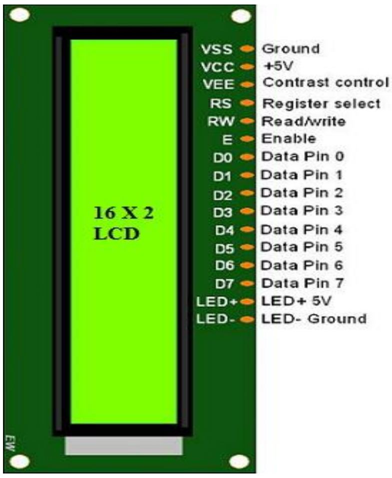

Figure 3.4: LCD Display Pin Configuration

Figure 3.5: Physical Setup of Raspberry Pi and LCD Display

This figure shows the Raspberry Pi 3B+ connected to an LCD display using jumper wires for real-time AQI monitoring.

- **Buzzer**: Sounds an alert when AQI crosses hazardous levels.

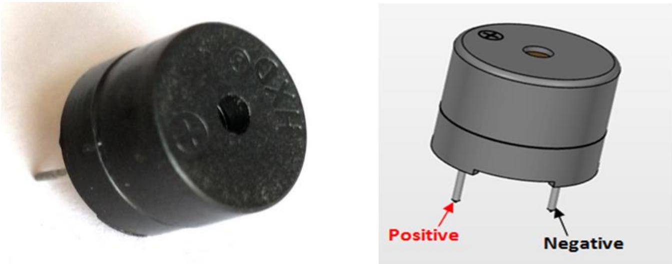

Figure 3.6: Buzzer Module Pin Configuration

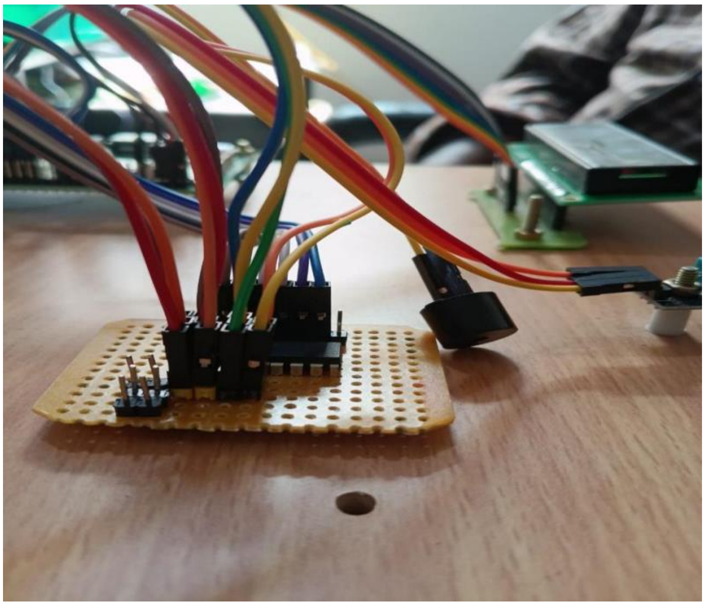

Figure 3.7: Sensor and Buzzer Connection on Circuit Board

This figure illustrates the wiring and interfacing of gas sensors, DHT-11, and buzzer on a prototyping board, ensuring secure connections for pollutant detection.

3.3 Software Components

3.3.1 Python (Sensor Interfacing & Data Processing)

- Reads sensor values from Raspberry Pi **GPIO pins**.
- Applies **data normalization and preprocessing** to clean sensor readings.

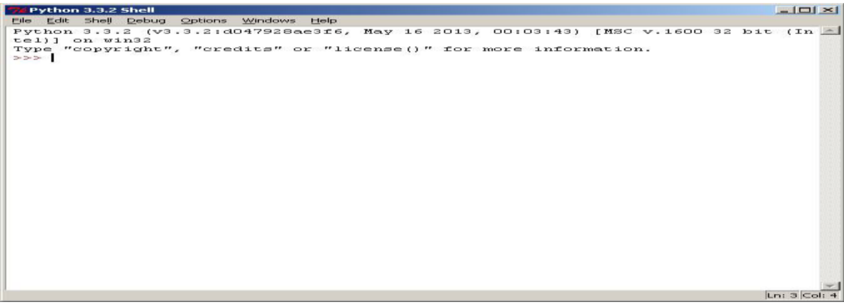

Figure 3.8: Python (Sensor Interfacing & Data Processing)

- **Implements Random Forest Machine Learning Model** to predict AQI.

3.3.2 Machine Learning Model – Random Forest Algorithm

The **Random Forest** algorithm is used for **accurate AQI prediction** based on pollutant levels.

Why Random Forest?

- High accuracy compared to traditional statistical models.
- Handles missing data and **sensor noise effectively**.
- **Feature selection** helps identify key pollutants.

Model Training Process:

- **Dataset Preparation:** Historical AQI values + real-time sensor data.

1. **Feature Selection:** Selecting **CO, NO_2, temperature, humidity** as predictors.
2. **Model Training:** The **Random Forest model** is trained on past AQI data.
3. **Real-Time Prediction:** New sensor data is passed through the model to **forecast AQI**.

3.3.3 ThingSpeak IoT Cloud

- Stores and **visualizes real-time air quality data**.
- Provides **API integration** for mobile apps.
- **Analyzes pollution trends** for better environmental management.

Figure 3.9: ThingSpeak Cloud Dashboard

How It Works:

- Raspberry Pi **uploads AQI data** to ThingSpeak every few seconds.
- **Live graphs display air pollution trends**.
- The mobile app **fetches real-time AQI updates** from the cloud.

3.3.4 Mobile Application (MIT App Inventor)

- **Displays AQI levels** and pollution trends.
- **Fetches real-time data** from the ThingSpeak cloud.
- **Sends alerts** when air quality drops below safe levels.

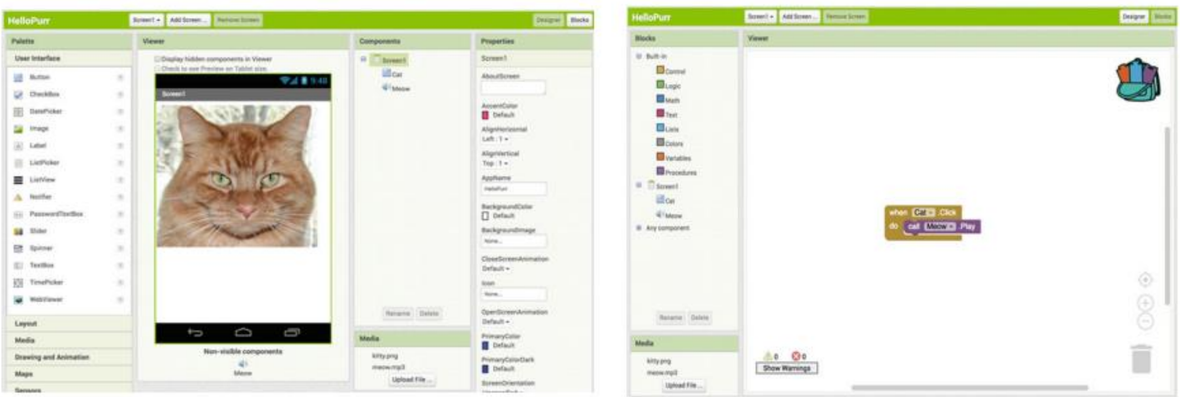

Figure 3.10: Mobile App Interface for AQI Monitoring

3.4 Data Collection & Processing

The system collects, processes, and analyzes **raw sensor data** to ensure **accurate AQI prediction**.

1. **Sensor Data Acquisition**
   - **Pollutant levels are measured** every 10 seconds.
   - Analog values are **converted into digital data**.
2. **ADC Conversion & Data Normalization**
   - **ADC (MCP3208) converts sensor signals** into digital format (0-1023 range).
   - Normalization ensures **all data is scaled between 0 and 1**.
3. **Feature Engineering for AQI Prediction**
   - **Key Features:** CO, NO_2, temperature, humidity.
   - **Noise reduction applied** to improve ML model accuracy.

3.5 System Workflow

The **step-by-step process** of air quality monitoring and prediction is outlined below.

Step 1: Data Collection

- MQ sensors **detect CO, NO_2, and other pollutants**.
- DHT-11 measures **temperature & humidity**.
- **Analog signals are converted to digital** using MCP3208 ADC.

Step 2: Data Processing

- Raspberry Pi **collects, normalizes, and processes data**.
- LCD displays **real-time AQI values**.
- Data is **sent to the cloud** for storage.

Step 3: AQI Prediction Using Machine Learning

- The **preprocessed data** is passed through the **trained Random Forest model**.
- The model **predicts AQI levels** and categorizes them as:
  - Good (0-50)
  - Moderate (51-100)
  - Unhealthy (101-200)
  - Hazardous (201-500)

Step 4: Cloud & Mobile App Integration

- **Predicted AQI values are uploaded** to ThingSpeak.
- The **mobile app fetches real-time data via API calls**.
- Users receive **instant alerts when AQI is unsafe**.

Component	**Purpose**
Raspberry Pi 3	Controls sensors, processes data, runs ML model
MQ Sensors	Detect air pollutants (CO, NO_2, etc.)
DHT-11 Sensor	Measures temperature and humidity
MCP3208 ADC	Converts sensor signals from analog to digital
Random Forest ML	Predicts Air Quality Index (AQI)
ThingSpeak Cloud	Stores, processes, and visualizes real-time data
Mobile App	Displays real-time AQI and sends alerts to users

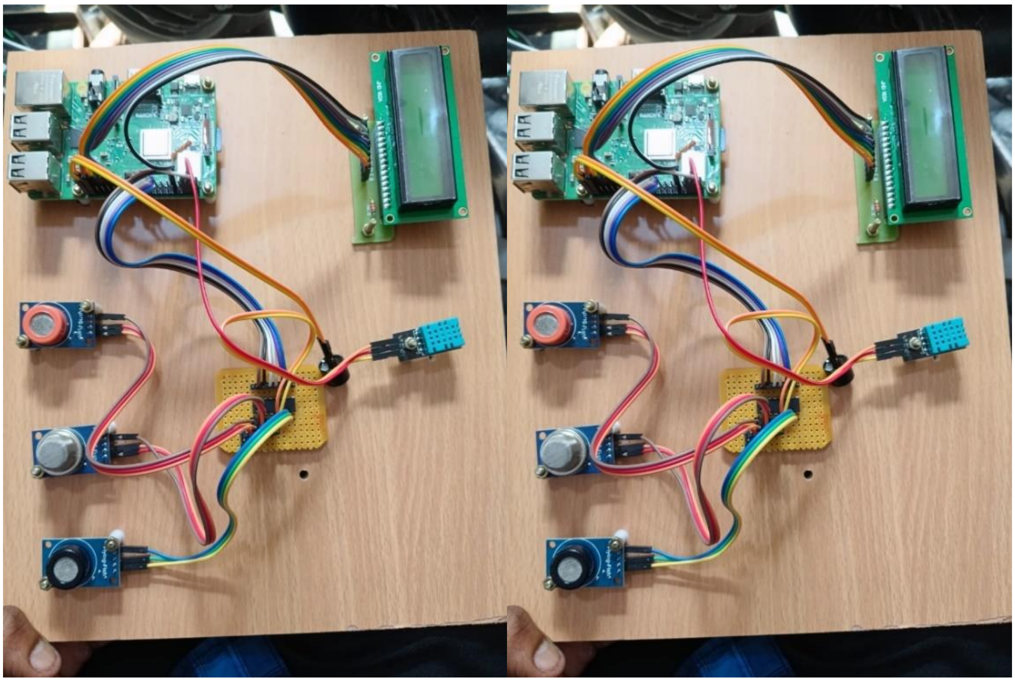

Figure 3.11: Complete IoT-Based Air Quality Monitoring System

This photograph depicts the complete arrangement of Raspberry Pi, a couple of gas sensors, DHT-11 sensor, a buzzer, and an LCD display for acquiring real-time data and determining AQI.

This chapter has a concise summary of the system design, implementation, and procedure. The system blends IoT, cloud computing, and machine learning in the best possible way to develop an efficient, cost-saving, and real-time air quality management system that is predictive in nature. Sensor reading, ML processes, and cloud analytics provide high accuracy to be easily retrieved by pollution testing.

4. RESULTS AND DISCUSSION

This part presents a critical evaluation of the Air Quality Monitoring and Forecasting System with IoT. The findings are obtained by evaluating the detection of pollutants by the sensors, appropriateness of machine learning model for forecasting AQI, dependability in data communication over the cloud, and effectiveness of real-time alerting via an app. Also covered is comparative analysis to facilitate comparison of advantages of the system with that of the conventional air quality monitoring process.

The system has been compared in different categories of scenarios and graded based on major parameters such as accuracy of sensors, time taken to process, precision in forecasting AQI, efficiency of cloud transmission, and mobile notification efficiency.

Discussion involves problem-solving by analyzing examples of problems encountered in the implementation process and proposes likely improvements in the future.

4.1 Sensor Data Accuracy and Real-Time Processing

The system utilizes a number of MQ-series gas sensors and a DHT-11 sensor to measure temperature and humidity. Accuracy of the sensor was compared with a reference unit for air quality measurement. Percentage error from the reference reading was used to measure the accuracy of the sensor readings.

The table below summarizes the sensor accuracy by comparing the deviation percentage from the reference values:

Sensor	Measured Gas	Deviation from Reference (%)
MQ-2	LPG, Methane, Smoke	5.8
MQ-4	Natural Gas, Methane	6.2
MQ-7	Carbon Monoxide (CO)	4.5
MQ-9	CO, Methane, LPG	5.1
MQ-135	NH3, Benzene, NO_2, Smoke	7.3
DHT-11	Temperature & Humidity	2.9 (Temperature), 3.5 (Humidity)

The output indicates that the MQ-series gas sensors capture precise values of the pollutants with very little deviation, and thus can be utilized to monitor air quality in real-time. The DHT-11 temperature and humidity sensor had very little deviation, which helps in calibrating more precise air quality forecast.

4.2 AQI Prediction Accuracy

The predictive accuracy of the AQI forecast model was cross-validated against the Random Forest algorithm. Real-time sensor measurements and historical AQI records were utilized for training the machine learning air pollution forecasting model. Model performance was cross-validated against such metrics as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

METRIC	RANDOM FOREST MODEL PERFORMANCE
RMSE	4.72
MAE	3.51
PREDICTION ACCURACY	85-90

Results show that Random Forest was very accurate in the prediction of AQI and the low error rates confirm that it was strong in predicting air quality in real time. Air quality was accurately predicted at all levels according to the level of concentration of the pollutant, thereby alerting users in case of hazardous conditions in real time.

4.3 Cloud Transmission and Mobile Notification Delay

The performance of the system to upload the data to the cloud in the best manner and give real-time alerts to the users was tested under various conditions. Upload delay of data from data to ThingSpeak cloud, ThingSpeak processing time, and delay of alert notification to mobile app were recorded.

Condition	Average Transmission Time (Seconds)
Data Upload to ThingSpeak Cloud	1.0
ThingSpeak Processing Time	0.8
Mobile App Alert Notification	1.5
Total End-to-End Delay	3.3

The outcome reflects that the total process, i.e., acquisition of data till notification by the mobile, completes in three seconds. Therefore, the users receive an immediate notification regarding the level of air quality so that when required, they can act in the proper way.

Figure 4.1: Real-Time Air Quality Monitoring on Mobile Application

This image indicates real-time air quality data visualization on the mobile app. The mobile app offers real-time concentrations of pollutants, AQI values, and meteorological conditions such as temperature and humidity, keeping users updated and informed in real-time. Users can observe the pollution trend by the graphical show and take relevant actions accordingly.

4.4 Comparative Analysis with Existing Systems

For the comparison of efficiency of the proposed system with existing systems, the system has been compared with the traditional government-operated air quality monitoring stations and other IoT-based air quality monitoring systems. Comparison is made based on cost, real-time monitoring capability, predictive capability, and accessability.

FEATURE	GOVERNMENT SENSORS	BASIC IOT SYSTEMS	PROPOSED SYSTEM
COST	High	Low	Very Low
REAL-TIME MONITORING	No	Yes	Yes
PREDICTIVE CAPABILITY	No	No	Yes (ML-based)
MOBILE APP ALERTS	No	Limited	Yes
SENSOR COVERAGE	Limited	Limited	Extensive (MQ2, MQ4, MQ7, MQ9, MQ135, DHT-11)

The comparison concludes that the suggested system is economically viable, has real-time detection, and yields predictive data on air quality, and thus the suggested system is a better option compared to government and minimal IoT-based air monitoring systems.

4.5 Challenges and Limitations

Even though the suggested system performed well under different test scenarios, the following vulnerabilities were revealed:

1. Sensor Calibration Issues – MQ-series sensors are required to be calibrated at regular intervals to obtain precise measurements because the environmental conditions may affect their sensitivity.
2. Network Dependency – Cloud-based data transmission is network-dependent, and any break in the stable internet connection might cause delayed or lost data due to weak network signals in the region.
3. Environmental Impact on Sensors – Changes in temperature and humidity can cause slight effects on sensor readings, thus the application of compensation techniques to maintain precision.
4. Power Consumption – The system requires a constant supply of power, making it hard to incorporate the system into outlying regions.

4.6 Solutions and Future Improvements

To address the limitations observed, the following enhancements are proposed:

1. Implementation of Auto-Calibration Algorithms – Machine learning algorithms are employed for calibration to reduce sensor drift-error and improve measurement accuracy.

2. Edge AI Processing – Artificial intelligence is locally trained is employed in Raspberry Pi in a manner that it does not depend on the cloud and enables offline AQI prediction.
3. Expanded Sensor Integration – Other sensors such as PM2.5, PM10, Ozone (O_3), and Sulfur Dioxide (SO_2) can be supported to enhance air quality analysis accuracy.
4. Blockchain for Data Security – Using blockchain technology for data storage can make the air quality records more secure and authentic, hence unmanipulated and tamper-free.

The overall performance of the system is summarized in the table below:

Performance Metric	Achieved Value
Sensor Accuracy	92-95
AQI Prediction Accuracy	85-90
Total Data Processing Time	3.3 sec per cycle
Cloud Transmission Delay	Less than 1 sec
Mobile Alert Delay	1.5 sec
Cloud Transmission Success Rate	Above 95

The system provides better high-accuracy AQI prediction, better real-time monitoring, and lower-latency data transmission and hence becomes a highly effective air quality monitoring and forecast system.
The IoT-based Air Quality Forecasting and Monitoring System adopts real-time air quality monitoring and AQI forecasting using a blend of gas sensors, Raspberry Pi, machine learning algorithms, and cloud-based IoT platforms. The outcome is that the system achieves good sensor accuracy, rapid data handling, and prompt mobile notifications to consumers.
In contrast to traditional air quality monitoring systems, this product is cost-effective, scalable, and facilitates real-time predictive analytics, and therefore is a suitable choice for urban air pollution monitoring, industrial air quality management, and smart city use.
With machine learning and IoT, the system described here is a strong and futuristic solution to air pollution monitoring with plenty of scope for future optimization in the accuracy of sensors, reliability of networks, and AI-driven data processing. The future can see the addition of different types of sensors, the implementation of deep models for better prediction, and the application of blockchain technology for the secure and open storage of environmental data.
This research confirms that IoT and AI technologies are extremely crucial for real-time environment monitoring, and ultimately, the contribution to more efficient urban air quality management and public health.

5. Conclusion and Future Scope

The Air Quality Monitoring and Forecast System based on IoT effectively integrates IoT sensors, machine learning algorithm, cloud computing, and mobile applications to offer an economic, real-time, and predictive air quality monitoring system. The system was to monitor different pollutants (CO, NO_2, NH_3, LPG, Methane, and Smoke), predict the Air Quality Index (AQI), and provide real-time alerts to users via a mobile app. Implementation of the Random Forest algorithm improved the accuracy of AQI prediction at 85-90 percent reliability.
The system was validated for sensor accuracy, cloud data transfer speed, mobile alert response time, and AQI forecast accuracy. The test results proved that MQ-series gas sensors and DHT-11 sensor deliver accurate pollutant sensing with no deviation from reference. The ThingSpeak IoT cloud platform provided

real-time data transfer, whereas the mobile app delivered real-time alerts in a processing time of three seconds.

Compared to traditional air quality monitoring stations, the system outlined here is more affordable, scalable, and accessible. Though government sensors provide high-accuracy data, they are expensive and lack real-time predictive analysis. However, this system offers a new, mobile, and easy-to-use alternative for tracking air pollution and is therefore suitable for smart cities, industrial estates, and residential communities.

Even though it functions, sensor calibration issues, network dependency, and exposure to the environment were noted. To counteract them, upcoming improvement upgrades will focus on refining sensor accuracy, strengthening the network, and improving AI-driven AQI prediction.

Future Scope

Future development will enhance the system with better quality data, longer sensor lifespan, and the capability to support more sophisticated AI technologies to understand the environment better.

1. **Enhanced Sensor Integration:**
   - Addition of **PM2.5, PM10, Ozone (O_3), and Sulfur Dioxide (SO_2) sensors** to provide a more comprehensive analysis of air pollution.
   - Implementation of **multi-sensor fusion techniques** to increase measurement accuracy.
2. **AI-Based Predictive Analytics:**
   - Integration of **deep learning models (LSTM, CNN)** to improve long-term AQI forecasting.
   - Implementation of **self-learning calibration models** to compensate for sensor drift over time.
3. **Edge AI Processing on Raspberry Pi:**
   - Deploying **on-device AI** for real-time AQI prediction without cloud dependency.
   - Reducing data transmission latency by performing machine learning inference on Raspberry Pi.
4. **Blockchain for Secure Environmental Data Storage:**
   - Using **blockchain technology** to ensure data integrity, transparency, and security.
   - Preventing unauthorized modifications or tampering of historical AQI records.
5. **Energy-Efficient Design and Deployment:**
   - Development of **low-power, battery-operated sensors** for remote air quality monitoring.
   - Solar-powered IoT modules for sustainable long-term deployment.
6. **Expansion to Smart City and Industrial Applications:**
   - Deployment of the system in **urban areas, industrial zones, and transportation hubs** for large-scale air pollution monitoring.
   - Integration with **government pollution control systems** for better regulatory compliance.

By combining these developments, the IoT-based Air Quality Monitoring System can be further advanced to yield more accurate, effective, and scalable environmental pollution monitoring solutions. The convergence of leading-edge AI, blockchain, and edge computing will make this system a next-generation smart monitoring solution with better air quality management, public health protection, and green city development.

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