

IoT Enabled Hyperlocal Air Quality Monitoring and Prediction System Using ESP32 & Machine Learning

Mr. Ayush A. Padmawar

s23_padmawar_ayush@mcmcen.ac.in

Mr. Gandharv S. Birkurwar

s23_birkurwar_gandharv@mcmcen.ac.in

Ms. Maithili V. Mangalagiri

mangalagiri_mv@mcmcen.ac.in

MGM's College of Engineering, Nanded
Department of Electronics & Telecommunication Engineering

Abstract: - Increasing pollution and its serious health implications demand more accessible and hyperlocal air quality monitoring solutions. This paper presents an IoT-enabled, low-cost air quality monitoring and prediction system using the ESP32 microcontroller, MQ135 gas sensor, and DHT22 temperature-humidity sensor. The system records environmental parameters at regular intervals and uploads them to a cloud database for real-time visualization through a custom online dashboard. A Long Short-Term Memory (LSTM) based recurrent neural network is incorporated to generate short-term air quality predictions, providing early insights into short-term AQI variations. The proposed system is cost-efficient, scalable, and suitable for residential and academic deployment.

Keywords: ESP32, Hyperlocal AQI, IoT, MQ135, DHT22, Machine Learning, Cloud Dashboard.

I. Introduction

Air pollution continues to rise globally, making localized monitoring systems essential for effective environmental awareness. Traditional air quality monitoring stations, although accurate, are limited in number and unable to capture micro-level variations caused by traffic congestion, indoor emissions, or localized industrial activity [1], [2]. As a result, large-

scale monitoring infrastructures often fail to represent actual exposure levels experienced by individuals at a community scale.

Recent advancements in Internet of Things (IoT) technologies have enabled the development of low-cost, distributed sensing nodes capable of real-time environmental monitoring and cloud-based data access [3][5]. In this work, an ESP32-based hyperlocal air quality monitoring system is proposed, integrating MQ135 and DHT22 sensors to measure gas concentration, temperature, and humidity. The collected data is transmitted to a cloud platform and visualized through a live dashboard. Additionally, a time-series based LSTM prediction model is employed to forecast short-term air quality trends using historical sensor data, enabling proactive environmental awareness and decision-making [7], [9]. The system aims to offer an affordable and scalable solution suitable for community-level and academic applications.

II. Literature Review

Several studies have demonstrated the effectiveness of IoT-based environmental monitoring systems for achieving low-cost and scalable air quality assessment [1][3]. MQ135 sensors, despite their moderate absolute accuracy, have been widely adopted for trend analysis and relative air quality monitoring when combined with

appropriate calibration techniques [4][8]. Similarly, ESP32 microcontrollers are frequently used in IoT applications due to their integrated Wi-Fi capabilities, low power consumption, and sufficient processing performance for real-time data acquisition and transmission [5][10].

Machine learning techniques such as Linear Regression, AR models, and Long Short-Term Memory (LSTM) networks have been extensively applied for short-term AQI forecasting [7][9][11]. Among these, LSTM networks are particularly suitable for air quality prediction due to their ability to capture short-term dependencies in time-series environmental data. However, many existing systems focus either on monitoring or prediction independently and lack a unified framework integrating sensing, cloud visualization, and machine learning-based forecasting. This work addresses these limitations by presenting an end-to-end hyperlocal monitoring pipeline.

III. System Architecture & Methodology

The proposed system is designed as a multi-layer IoT architecture consisting of sensing, communication, storage, analytics, and visualization layers.

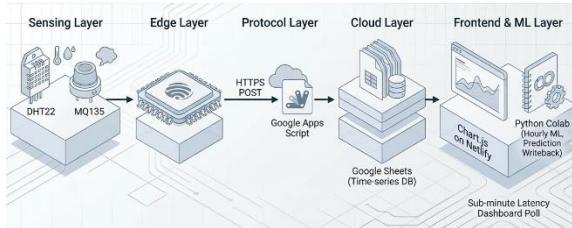


Fig.1 Overall Architecture of the IoT-Enabled Hyperlocal Air Quality Monitoring System

A. Hardware Setup

The ESP32 microcontroller serves as the central controller of the system, interfacing

with the MQ135 gas sensor for air quality measurement and the DHT22 sensor for temperature and humidity sensing. These sensors provide continuous environmental data, which is periodically sampled and processed by the ESP32 before transmission to the cloud.

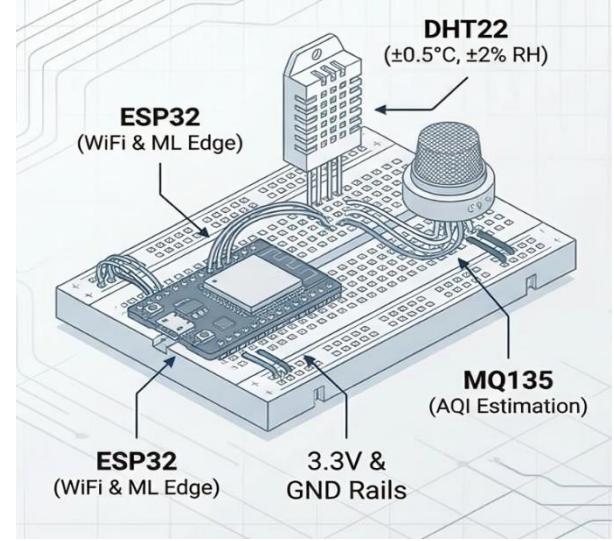


Fig.2 Hardware Implementation of the Proposed System Using ESP32, DHT22, and MQ135 Sensors

B. Data Communication

The ESP32 uploads sensor data to a cloud backend using Wi-Fi-based HTTP communication at fixed intervals. Cloud platforms such as Google Sheets or Firebase are used to store timestamped sensor readings, enabling remote access, long-term storage, and subsequent data analysis[5][10].

	Date	Time	Humidity (%)	Temperature (°C)	AQI	Category
10	2023-11-11	13:21:08	27.1	40.6	106	Good
11	2023-11-11	13:21:12	27.1	40.6	106	Good
12	2023-11-11	13:21:16	27.1	40.6	106	Good
13	2023-11-11	13:21:20	27.1	40.6	106	Good
14	2023-11-11	13:21:24	27.1	40.6	106	Good
15	2023-11-11	13:21:28	27.1	40.6	106	Good
16	2023-11-11	13:21:32	27.1	40.6	106	Good
17	2023-11-11	13:21:36	27.1	40.6	106	Good
18	2023-11-11	13:21:40	27.1	40.6	106	Good
19	2023-11-11	13:21:44	27.1	40.6	106	Good
20	2023-11-11	13:21:48	27.1	40.6	106	Good
21	2023-11-11	13:21:52	27.1	40.6	106	Good
22	2023-11-11	13:21:56	27.1	40.6	106	Good
23	2023-11-11	13:22:00	27.1	40.6	106	Good
24	2023-11-11	13:22:04	27.1	40.6	106	Good
25	2023-11-11	13:22:08	27.1	40.6	106	Good
26	2023-11-11	13:22:12	27.1	40.6	106	Good
27	2023-11-11	13:22:16	27.1	40.6	106	Good
28	2023-11-11	13:22:20	27.1	40.6	106	Good
29	2023-11-11	13:22:24	27.1	40.6	106	Good
30	2023-11-11	13:22:28	27.1	40.6	106	Good
31	2023-11-11	13:22:32	27.1	40.6	106	Good
32	2023-11-11	13:22:36	27.1	40.6	106	Good
33	2023-11-11	13:22:40	27.1	40.6	106	Good
34	2023-11-11	13:22:44	27.1	40.6	106	Good
35	2023-11-11	13:22:48	27.1	40.6	106	Good
36	2023-11-11	13:22:52	27.1	40.6	106	Good
37	2023-11-11	13:22:56	27.1	40.6	106	Good
38	2023-11-11	13:23:00	27.1	40.6	106	Good
39	2023-11-11	13:23:04	27.1	40.6	106	Good
40	2023-11-11	13:23:08	27.1	40.6	106	Good
41	2023-11-11	13:23:12	27.1	40.6	106	Good
42	2023-11-11	13:23:16	27.1	40.6	106	Good
43	2023-11-11	13:23:20	27.1	40.6	106	Good
44	2023-11-11	13:23:24	27.1	40.6	106	Good
45	2023-11-11	13:23:28	27.1	40.6	106	Good
46	2023-11-11	13:23:32	27.1	40.6	106	Good
47	2023-11-11	13:23:36	27.1	40.6	106	Good
48	2023-11-11	13:23:40	27.1	40.6	106	Good
49	2023-11-11	13:23:44	27.1	40.6	106	Good
50	2023-11-11	13:23:48	27.1	40.6	106	Good
51	2023-11-11	13:23:52	27.1	40.6	106	Good
52	2023-11-11	13:23:56	27.1	40.6	106	Good
53	2023-11-11	13:24:00	27.1	40.6	106	Good
54	2023-11-11	13:24:04	27.1	40.6	106	Good
55	2023-11-11	13:24:08	27.1	40.6	106	Good
56	2023-11-11	13:24:12	27.1	40.6	106	Good
57	2023-11-11	13:24:16	27.1	40.6	106	Good
58	2023-11-11	13:24:20	27.1	40.6	106	Good
59	2023-11-11	13:24:24	27.1	40.6	106	Good
60	2023-11-11	13:24:28	27.1	40.6	106	Good
61	2023-11-11	13:24:32	27.1	40.6	106	Good
62	2023-11-11	13:24:36	27.1	40.6	106	Good
63	2023-11-11	13:24:40	27.1	40.6	106	Good
64	2023-11-11	13:24:44	27.1	40.6	106	Good
65	2023-11-11	13:24:48	27.1	40.6	106	Good
66	2023-11-11	13:24:52	27.1	40.6	106	Good
67	2023-11-11	13:24:56	27.1	40.6	106	Good
68	2023-11-11	13:25:00	27.1	40.6	106	Good
69	2023-11-11	13:25:04	27.1	40.6	106	Good
70	2023-11-11	13:25:08	27.1	40.6	106	Good
71	2023-11-11	13:25:12	27.1	40.6	106	Good
72	2023-11-11	13:25:16	27.1	40.6	106	Good
73	2023-11-11	13:25:20	27.1	40.6	106	Good
74	2023-11-11	13:25:24	27.1	40.6	106	Good
75	2023-11-11	13:25:28	27.1	40.6	106	Good
76	2023-11-11	13:25:32	27.1	40.6	106	Good
77	2023-11-11	13:25:36	27.1	40.6	106	Good
78	2023-11-11	13:25:40	27.1	40.6	106	Good
79	2023-11-11	13:25:44	27.1	40.6	106	Good
80	2023-11-11	13:25:48	27.1	40.6	106	Good
81	2023-11-11	13:25:52	27.1	40.6	106	Good
82	2023-11-11	13:25:56	27.1	40.6	106	Good
83	2023-11-11	13:26:00	27.1	40.6	106	Good
84	2023-11-11	13:26:04	27.1	40.6	106	Good
85	2023-11-11	13:26:08	27.1	40.6	106	Good
86	2023-11-11	13:26:12	27.1	40.6	106	Good
87	2023-11-11	13:26:16	27.1	40.6	106	Good
88	2023-11-11	13:26:20	27.1	40.6	106	Good
89	2023-11-11	13:26:24	27.1	40.6	106	Good
90	2023-11-11	13:26:28	27.1	40.6	106	Good
91	2023-11-11	13:26:32	27.1	40.6	106	Good
92	2023-11-11	13:26:36	27.1	40.6	106	Good
93	2023-11-11	13:26:40	27.1	40.6	106	Good
94	2023-11-11	13:26:44	27.1	40.6	106	Good
95	2023-11-11	13:26:48	27.1	40.6	106	Good
96	2023-11-11	13:26:52	27.1	40.6	106	Good
97	2023-11-11	13:26:56	27.1	40.6	106	Good
98	2023-11-11	13:27:00	27.1	40.6	106	Good
99	2023-11-11	13:27:04	27.1	40.6	106	Good
100	2023-11-11	13:27:08	27.1	40.6	106	Good
101	2023-11-11	13:27:12	27.1	40.6	106	Good
102	2023-11-11	13:27:16	27.1	40.6	106	Good
103	2023-11-11	13:27:20	27.1	40.6	106	Good
104	2023-11-11	13:27:24	27.1	40.6	106	Good
105	2023-11-11	13:27:28	27.1	40.6	106	Good
106	2023-11-11	13:27:32	27.1	40.6	106	Good
107	2023-11-11	13:27:36	27.1	40.6	106	Good
108	2023-11-11	13:27:40	27.1	40.6	106	Good
109	2023-11-11	13:27:44	27.1	40.6	106	Good
110	2023-11-11	13:27:48	27.1	40.6	106	Good
111	2023-11-11	13:27:52	27.1	40.6	106	Good
112	2023-11-11	13:27:56	27.1	40.6	106	Good
113	2023-11-11	13:28:00	27.1	40.6	106	Good
114	2023-11-11	13:28:04	27.1	40.6	106	Good
115	2023-11-11	13:28:08	27.1	40.6	106	Good
116	2023-11-11	13:28:12	27.1	40.6	106	Good
117	2023-11-11	13:28:16	27.1	40.6	106	Good
118	2023-11-11	13:28:20	27.1	40.6	106	Good
119	2023-11-11	13:28:24	27.1	40.6	106	Good
120	2023-11-11	13:28:28	27.1	40.6	106	Good
121	2023-11-11	13:28:32	27.1	40.6	106	Good
122	2023-11-11	13:28:36	27.1	40.6	106	Good
123	2023-11-11	13:28:40	27.1	40.6	106	Good
124	2023-11-11	13:28:44	27.1	40.6	106	Good
125	2023-11-11	13:28:48	27.1	40.6	106	Good
126	2023-11-11	13:28:52	27.1	40.6	106	Good
127	2023-11-11	13:28:56	27.1	40.6	106	Good
128	2023-11-11	13:29:00	27.1	40.6	106	Good
129	2023-11-11	13:29:04	27.1	40.6	106	Good
130	2023-11-11	13:29:08	27.1	40.6	106	Good
131	2023-11-11	13:29:12	27.1	40.6	106	Good
132	2023-11-11	13:29:16	27.1	40.6	106	Good
133	2023-11-11	13:29:20	27.1	40.6	106	Good
134	2023-11-11	13:29:24	27.1	40.6	106	Good
135	2023-11-11	13:29:28	27.1	40.6	106	Good
136	2023-11-11	13:29:32	27.1	40.6	106	Good
137	2023-11-11	13:29:36	27.1	40.6	106	Good
138	2023-11-11	13:29:40	27.1	40.6	106	Good
139	2023-11-11	13:29:44	27.1	40.6	106	Good
140	2023-11-11	13:29:48	27.1	40.6	106	Good
141	2023-11-11	13:29:52	27.1	40.6	106	Good
142	2023-11-11	13:29:56	27.1	40.6	106	Good
143	2023-11-11	13:30:00	27.1	40.6	106	Good
144	2023-11-11	13:30:04	27.1	40.6	106	Good
145	2023-11-11	13:30:08	27.1	40.6	106	Good
146	2023-11-11	13:30:12	27.1	40.6	106	Good
147	2023-11-11	13:30:16	27.1	40.6	106	Good
148	2023-11-11	13:30:20	27.1	40.6	106	Good
149	2023-11-11	13:30:24	27.1	40.6	106	Good
150	2023-11-1					

C. Machine Learning Prediction Model

To enable short-term forecasting of air quality trends, a Long Short-Term Memory (LSTM) based recurrent neural network is employed. LSTM networks are well suited for time-series data as they can effectively model short-term dependencies present in environmental parameters such as temperature, humidity, and AQI [7][9][11].

The model is trained offline using historical sensor data stored in the cloud database. Input features include recent sequences of temperature, humidity, and estimated AQI values, while the output corresponds to short-term AQI predictions. The LSTM model is utilized for trend forecasting and early indication of air quality variations rather than regulatory-grade AQI estimation.

D. Dashboard

A custom web-based dashboard developed using HTML, JavaScript, and Chart.js visualizes real-time and historical sensor data retrieved from the cloud database. The dashboard provides numerical indicators and graphical representations of environmental parameters, enhancing system usability and interpretability.

IV. Result

The proposed system successfully recorded and transmitted environmental data to the cloud backend, with real-time updates reflected on the dashboard. The collected dataset enabled continuous monitoring of temperature, humidity, and AQI variations at a hyperlocal level.

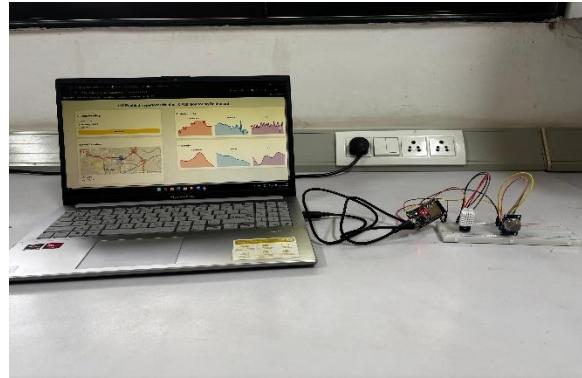


Fig.4 Real-Time Monitoring and LSTM-Based Prediction Dashboard

The LSTM-based prediction model generated short-term forecasts that closely followed recent data trends, demonstrating the practical feasibility of integrating machine learning for early air quality trend analysis [7], [11]. The dashboard interface effectively displayed live readings and predictions, validating the reliability and practical applicability of the system.

V. Security & Challenges

To ensure secure data transmission, encrypted Wi-Fi communication and controlled cloud API access mechanisms were employed [5]. Regular firmware updates further enhance system security. Key challenges encountered include sensor drift associated with the MQ135 sensor, Wi-Fi connectivity interruptions, environmental noise affecting prediction accuracy, and the requirement for a stable power supply for continuous operation [4][8].

VI. Future Scope

Future enhancements include the integration of precise particulate matter sensors (PM2.5/PM10), solar-powered outdoor deployment, on-device prediction using TinyML techniques, GPS-based pollution mapping, mobile application development with alert mechanisms, and deployment of a multi-node distributed monitoring network [7][9].

VII. Conclusion

This work presents a compact and cost-effective hyperlocal air quality monitoring system combining ESP32-based sensing, cloud storage, real-time dashboard visualization, and machine learning prediction. Despite minor limitations in sensor accuracy and connectivity dependency, the system is effective for residential and academic environments. The work forms a foundation for future large-scale smart-city environmental monitoring solutions.

References

- [1] S. Borah and A. Nath, “Air quality monitoring system based on IoT using ESP32,” *International Conference on Computational Intelligence and IoT*, 2021, pp. 112–118.
- [2] S. Kumar, R. Anbalagan, and P. Singh, “Survey on IoT-based air pollution monitoring systems,” *Journal of Ambient Intelligence and Humanized Computing*, 2022.
- [3] P. Chhabra, M. Saini, and S. Gupta, “Real-time air quality monitoring using low-cost sensors and cloud computing,” *2020 IEEE International Conference on IoT and Applications (ICIOT)*, pp. 87–92.
- [4] A. Kumar and V. Arora, “IoT-based environmental monitoring using MQ series sensors,” *International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)*, 2021, pp. 559–564.
- [5] R. R. Rout and S. Mishra, “Cloud-assisted air pollution monitoring and alerting system using ESP32,” *Proceedings of the IEEE International Conference on Smart Electronics and Communication (ICOSEC)*, 2020, pp. 109–115.
- [6] F. Tsow et al., “A wearable and low-cost air quality monitoring system,” *Sensors and Actuators B: Chemical*, vol. 240, pp. 578–587, 2017.
- [7] S. Raju and K. K. Nair, “Machine learning-based air quality prediction: A review,” *International Journal of Environmental Science and Technology*, 2021.
- [8] A. De Vito et al., “Calibration of low-cost gas sensors for air quality monitoring: A review,” *Sensors*, vol. 20, no. 9, 2020, pp. 1–24.
- [9] B. H. Choi, J. Park, and H. Lee, “Air quality prediction using LSTM and GRU neural networks,” *IEEE International Conference on Big Data and Smart Computing (BigComp)*, 2019, pp. 1–6.
- [10] P. Singh and R. Sharma, “Implementation of an IoT-based air quality monitoring system using ESP32 and cloud services,” *International Conference on Emerging Smart Computing and Informatics (ESCI)*, 2022, pp. 342–347.
- [11] J. Ma, X. Yu, and A. Chen, “Short-term air quality forecasting using machine learning techniques,” *IEEE Access*, vol. 8, pp. 225–234, 2020.