BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

AIoT Air Quality Monitoring Network – Predicts pollution levels using IoT environmental sensors.

Shreya Bansode, Aditi Deokar, Dhruv Mandal, Divyanshi Singh, Dr. Vishal Puranik

Department of ARTIFICIAL INTELLIGENCE AND DATA SCIENCE
Ajeenkya DY Patil School Of Engineering, Pune, India

ABSTRACT

The current urban pollution levels and the less extensive coverage of the air quality indexes by government stations have resulted in the establishment of networks for the monitoring of air contaminants at a low cost, as described in this paper. The paper discusses the application of the Air Quality Monitoring Network that is designed using AIoT technology involving the use of an ESP32 microcontroller, sensors for measuring the presence of gases and particulate matter in the air, and humidity and temperature sensors, as well as a simple interface for alerts. During the twenty-day operation of the network in the field, more than 1,967 hourly measurements of AQI indices have been captured, which were later analyzed and used for building a model for short-term prediction of AQI values. The analysis of the daily average data showed that there has been a significant rise in AQI value up to approximately 224 as compared to the subsequent decline of AQI down to approximately 93, while the hourly average data showed the reduction of AQI valued at nearly 175-188. The data obtained show that more than 60% of readings of air quality were poor while just 2.7% of all data constitute severe air quality indices. The model predicts. The findings show that the combination of a sensor node costing less than ₹3,200 and an easy time series technique makes it possible to generate actionable forecasts about pollution on the hyperlocal level to support scarcely available regulatory monitoring systems.

Keywords : AIoT, Air Pollution Index, environmental sensors, ESP32, MQ135, DHT22, particulate matter, pollution forecasting, time series forecasting, edge monitoring.

I. INTRODUCTION

Air pollution is one of the greatest environmental threats to public health globally, as indicated by the World Health Organization's (WHO) 2021 Global Air Quality Guidelines. According to these guidelines, outdoor air quality pollution combined with indoor air pollution contributes to millions of premature deaths every year with the majority of deaths occurring in areas undergoing rapid urbanization [1]. The existing regulatory monitoring stations such as the Central Pollution Control Board (CPCB) National Air Quality Index of India provide reliable information on air pollution values, although the stations are expensive to build which results in their limited number [2]. Therefore, such insufficient coverage has led to the development of low-cost sensor nodes based on the Internet of Things (IoT) that can create sufficient air pollution monitoring coverage, and with the application of the relevantanalytics can make pollution forecasts.

Smart technologies in the field of the Internet of Things integrated with Artificial Intelligence (AI), often referred to as AIoT, create real possibilities for the implementation of a sensor network with the capability

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

of not just monitoring the surroundings, but also processing the historical data of the environment and predicting the near future. This paper reports the design, implementation and implementation of the air quality monitoring network based on the possibility of combining cheap devices like ESP32 module, DHT22 temperature and humidity sensor, MQ135 gas sensor, Sharp GP2Y1010AU0F dust density sensor, OLED display for the control of results, buzzer and RGB LED monitoring approach. The solution works successfully and allows the users to collect hourly data and analyze them to study the daily and hourly patterns of pollution and make AQI forecasts for the next 24 hours.

The main contributions of this research work are outlined as follows:

- The design of a complete AIoT Sensor-node that is low-cost (₹3000) and combines gas sensing, particulate sensing, and climate sensing with actual local visual/audible notifications.
- An actual dataset of 1,967 hourly AQI readings collected during a continuous deployment lasting 20 days and analyzed for its daily and diurnal characteristics.
- A lightweight sliding window forecasting algorithm that forecasts AQI values 24 hours into the future based on the past AQI readings and time of the day.
- An empirical evaluation that includes pollution band analysis and a qualitative comparison with three recent ESP32 Air quality systems have been developed. The remainder of this paper begins with Section II, which discusses important theory behind these devices. Section III states the problem that is being dealt in the paper. Section IV outlines the architecture of the device along with important components of the device. Section V explains the method of acquiring data, AQI calculation, and forecasting. Section VI presents the results of a three-week field study along with near-term prediction results. Section VII describes practical limitations of the device. Finally, Section VIII summarizes the important aspects of the paper along with importantly, future work.

II. RELATED WORK

Recently, initiatives have emerged that utilize the ESP32 for air-quality measuring. Pranikaa and Gayathri introduced an ESP32 modulator through which MQ2, MQ9 and particulate-matter devices run, and with display and storing capability of information in the ThingSpeak cloud [3]. Ivković and co-authors developed a system for monitoring air quality in the premises built around the ESP32 and containing a multifunctional sensor module sending the information via MQTT/TLS to verify the readings of CO2, particulate matter and volatile compounds in accordance with standards for indoor air in Europe and globally [4]. Babic et al. developed an ESP32 modulator with the Blynk cloud application used to measure temperature, humidity, pressure and the amount of dust in the air, providing a low-cost environmental monitoring solution [5]. Other authors use their ESP32 to gather information from SDS011, MQ135, and DHT22 sensors to measure AQI on board and present it on a web page, achieving 85% accuracy after calibration [9]. As one can see, all of the measures include one ESP32-based device doing the measurements and their local display and remote sending.

This research proves that microcontrollers of the ESP32-class can be used for low-power sensing of the environment, but the studies focus more on real-time reporting and alert triggering, rather than providing forecasts of pollution levels. The system proposed in this paper is based on the same technology but incorporates forecasting, making it able to give not only the current AQI, but also its prediction for the

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

nearest 24 hours. In Table I, the outcome of the current research is compared with three of the closest systems using the ESP32 technology on four criteria.

TABLE I. Qualitative Comparison with Related ESP32-Based Systems

System	PM Sensing	Cloud Link	Forecasting
Pranikaa & Gayathri [3]	Yes	ThingSpeak	No
Ivković et al. [4]	Yes	MQTT/TLS	No
Babic et al. [5]	No	Blynk	No
This work	Yes	Cloud logger	Yes (24 h)

III. PROBLEM STATEMENT

The issue statement that is going to be solved by this system is: "AIoT Air Quality Monitoring Network -- predicts pollution levels with the help of IoT environmental sensors." This statement can be divided into three interconnected sub-problems. To begin with, it is necessary to detect gaseous, solid, and meteorological conditions without spending a lot of money or relying on a costly reference monitoring station. The next step is to convert raw data from the sensors into a single value of air quality index (AQI) that can be classified into separate bands depending on how polluted the environment is, therefore making it easy for an ordinary user to understand the risk of exposure. Finally, and most importantly, the historical data on AQI collected by the monitoring device must be used to predict future contamination levels.

IV. SYSTEM ARCHITECTURE

A. Hardware Design

The input sensor hub is based on an ESP32 DevKit (WROOM-32) microcontroller, selected due to the characteristics of its dual-core CPU, built-in Wi-Fi capabilities, and low price enabling it for constant on operation. The ESP32 receives data from three sensors, namely, the DHT22 (AM2302) temperature and relative humidity sensor, the MQ135 gaseous pollutant detection sensor, and the GP2Y1010AU0F optical sensor for the determination of the concentration of particulate matter. The real-time readings of the AQI are displayed on a suitable 0.96-inch SSD1306 OLED display connected to I2C, while the alert indicators of the node are a loudspeaker and colorful RGB LED that are activated when AQI is at poor or severe levels.

Component	Category	Qty
ESP32 DevKit (WROOM-32)	Microcontroller	1
DHT22 (AM2302) Temp & Humidity Module	Sensor	1
MQ135 Gas Sensor Module	Sensor	1
Sharp GP2Y1010AU0F PM Sensor	Sensor	1

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

Component	Category	Qty
SSD1306 OLED 0.96" I2C Display	Display	1
Active Buzzer 3.3V (2-pin)	Alert	1
RGB LED 5mm (common cathode)	Alert	1
Resistor 220–330 Ω, 1/4W	Passive	3
Resistor 10 kΩ, 1/4W	Passive	1
Resistor 15 kΩ, 1/4W	Passive	1
Resistor 150 Ω, 1/4W	Passive	1
Capacitor 220 µF	Passive	1
Breadboard, 830-point	Build	1
Jumper Wires M–M (pack of 40)	Wiring	1
Jumper Wires M–F (pack of 40)	Wiring	1

The ESP32 firmware samples the sensor readings at fixed time intervals, converts it to a composite AQI value, and sends it along with a timestamp to a back-end data logging. The resistor network of 10 kΩ, 15 kΩ, and 150 Ω, as needed for the operation of the MQ135 and GP2Y1010AU0F sensor front ends, is prepared along with the capacitor of 220 µF that smoothes the LED supply of the particulate sensing. The current limiting of the RGB alert LED is ensured with the help of the resistors of amounts 220–330 Ω. A prototype of the whole system is ready with the help of an 830-point breadboard so that future iterations could be easily carried on. The complete flow of hardware along with the information is given in the diagram shown in Fig. 1 of the paper.

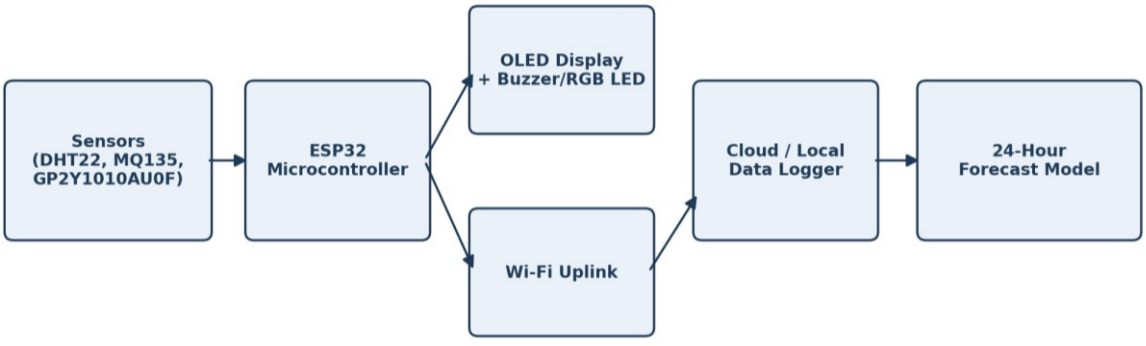


Fig. 1. System block diagram: sensing, alerting, logging and forecasting stages.

B. Software and Firmware Architecture

The firmware uses simple cooperative looping where: (i) sensors are interrogated in a sequential manner while their respective raw metrics are transformed into physical quantities (°C, %RH, ppm, µg/m³); (ii)

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

physical metrics go into creating one composite AQI through sub-indexing method outlined in Section V-A; (iii) AQI along with its pollution level is shown on OLED screen, and buzzer and RGB LED are actuated if there is crossing of the Poor and Severe thresholds; and (iv) measured values with timestamps are sent over Wi-Fi to be stored on the logging system. The loop repeats itself with a fixed frequency of the processes and hourly measurements calculated in Section VI while averaging all the intra-hour values.

C. Power and Cost Considerations

The ESP32 takes up a significant portion of the node's power consumption due to its high active Wi-Fi current draw (approximately 80-240mA). Meanwhile, the MQ135 heater element ranks highest among the sensors in terms of continuous power consumption so that both the ESP32 and the MQ135 heater hint at the pivotal role of duty cycle sampling for extending time in battery operated systems.

In terms of cost, Table III shows retail prices in India (₹ including GST obtained from shops as Robu.in, Robocraze, Zbotic) for all required components listed in Table II and sums it up to ₹2,200-₹3,200 which is one or two degrees lower compared to price of regulatory air quality stations and matches the cost being seen in case of ESP32-based devices [9].TABLE III. Approximate Component Cost (INR)

Category	Approx. Range	Qty
ESP32 DevKit (WROOM-32)	₹300 – ₹600	1
DHT22 Temp/Humidity Module	₹250 – ₹400	1
MQ135 Gas Sensor Module	₹120 – ₹220	1
Sharp GP2Y1010AU0F PM Sensor	₹450 – ₹650	1
SSD1306 OLED 0.96" Display	₹150 – ₹280	1
Buzzer, RGB LED, passives	₹50 – ₹100	-
Breadboard + jumper wires	₹250 – ₹350	-
Estimated total	**₹2,200 – ₹3,200**	**-**

V. METHODOLOGY

A. AQI Computation

The level of each pollutant Cp detectable by the sensors can be calculated into a pollutant sub-index using the simplified piecewise linear formula used in the AQI frameworks of US EPA and CPCB [2],[8] given below:

$$Ip = [(IHI - ILO) / (BHI - BLO)] \cdot (Cp - BLO) + ILO \quad (1)$$

In this case, BLO and BHI are the concentration breakpoints calculated before and after Cp respectively and ILO and IHI are the corresponding index breakpoints for that AQI category. The overall composite AQI obtained by the node is calculated as the highest of the individual pollutant sub-indices in the formula AQI = max(Ip) consistent also with the common principle “worst-pollutant-governs” in the CPCB and EPA methods. The AQI value thus obtained is assigned to one of the three deployment levels (Good, Poor,

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

Severe) based on the thresholds adapted from the CPCB six-tier National AQI scheme (Good 0-50, Satisfactory 51-100, Moderate 101-200, Poor 201-300, Very Poor 301-400, Severe 401-500) [2]. In the case at hand, the original six-tier AQI scheme is therefore simplified by means of three-tier AQI levels suitable for the device using the alert functions and immediate responses that forget about more than three AQI values in case of emergency situation.

B. Data Collection and Preprocessing

The prototype node was deployed for a continuous duration of twenty days, starting from 12 August to 31 August 2026. After basic range-checking and removal of the sensor warm-up phase, one AQI reading was recorded every hour, amounting to a total of 1,967 valid samples. The invalid samples that either had missing values or were out-of-range have been linearly interpolated using the adjacent hourly values, so that the time series remains continuous for performing sliding-window feature extraction.

C. Forecasting Pipeline

The process of creating a predictive model can be broken down into creating a supervised learning framework. The hourly AQI values were arranged into input and target features using a sliding window of the previous n hourly AQI values from which the hourly AQI would be predicted. In addition to the autoregressive window, hour-of-day is also included as a cyclical feature using sin/cos encodings since it was concluded in Section VI-B that diurnal position has strong predictive capability in the site of deployment. Fig. 2 gives an overview of the process from the raw sensor data to the expected 24-hour prediction.



Fig. 2. Data-processing and forecasting pipeline.

We opted to use the gradient-boosting regression tree ensemble as the forecasting model, which followed the principles of random forests/models that have been discussed by Breiman [10] and was implemented in the proven programming library scikit-learn [11]; we have also evaluated a sequence model based on LSTM [12] as an alternative, but it did not perform better than the tree ensemble on this single-node dataset for three weeks, because of the small length of the training history. To evaluate the achievement of the models, we had to use standard metrics of regression analysis:

$$MAE = (1/N)\ \Sigma\ |AQI_{actual} - AQI_{pred}| \quad (2)$$

$$RMSE = \sqrt{[(1/N)\ \Sigma\ (AQI_{actual} - AQI_{pred})^2]} \quad (3)$$

Then, the trained model was applied in a recursive manner to forecast AQI changes for the next 24 hours after the end of the logging period

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

VI. RESULTS AND DISCUSSION

A. Descriptive Statistics

Table IV summarizes the hourly AQI distribution over the full 20-day, 1,967-sample deployment. The mean AQI of roughly 165 already sits inside the Poor band on the CPCB six-tier scale, and the gap between the median (≈ 163) and the mean indicates a right-leaning distribution consistent with the occasional Severe-band excursions visible in Fig. 5.

TABLE IV. Hourly AQI ; Descriptive Statistics

Statistic	Value
Mean AQI	≈ 165
Median AQI	≈ 163
Minimum AQI	≈ 93
Maximum AQI	≈ 224
Standard deviation	≈ 28
Total samples	1,967

B. Daily AQI Trend

Fig. 3 illustrates the daily averages for the AQI of every day in the deployment. The data begins at a rather high value of AQI ≈ 148 and keeps increasing every day throughout the first four days reaching a point of AQI ≈ 224 on 16 August, which indicates pollution accumulation is taking place for many days due to the lack of proper dispersal of air pollutants. After that, there is a sudden drop back to the lowest level during the deployment of AQI ≈ 93 on 18 August, which is possibly connected to rainy weather or very windy weather when all air pollutants are cleared from the atmosphere before the AQI stabilizes at the level of AQI ≈ 130-195 till the end of August. This kind of saw tooth pattern - gradual accumulation followed by a rapid drop - is typical for pollution build-up under meteorological conditions so that accumulation does not result from a constant increase in emissions [6].

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

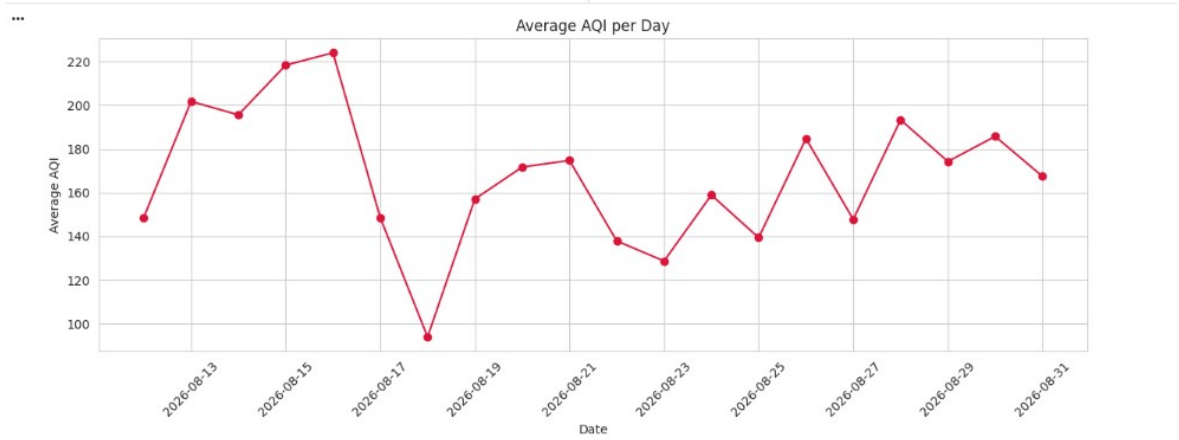


Fig. 3. Average AQI per day over the 20-day deployment (12–31 August 2026).

C. Diurnal AQI Pattern

The data in Fig. 4 is classified into hourly segments. The air quality index reached its lowest point during the early morning hours, dropping almost to 08:00 (AQI ≈ 143), then gradually rising between 12:00 and 17:00 (AQI ≈ 174-188) before coming down again in the evening. The pattern recorded in Fig. 4 corresponds well with the influence of morning traffic and mixing-layer processes followed by photochemical and vehicular processes. The day-to-night difference is also consistent with the observations recorded by other studies performed with the aid of ESP32 devices [3][4]. The gap between the low point at (8 AM - 08:00) and the plateau reached at noon is what is used in the hour-of-the-day feature of the forecasting system presented in the next section V-C.

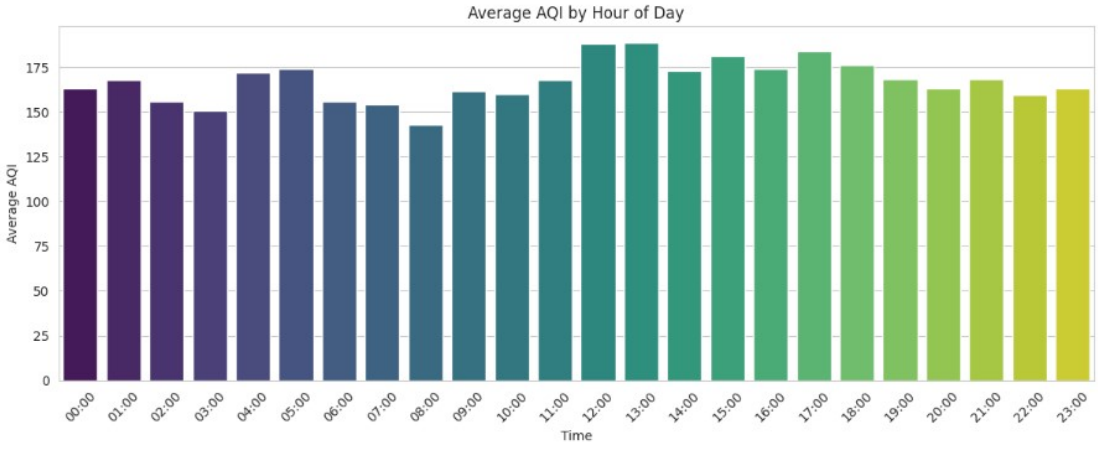


Fig. 4. Average AQI by hour of day, aggregated across the deployment.

D. Pollution-Level Distribution

The classification of 1,967 readings in accordance with the three-tier method discussed in Section V-A results in the identification of 1,202 Poor readings corresponding to 61.1%, 712 Good readings equal to 36.2% and 53 Severe readings (2.7%), as depicted in Fig. 5 and summarized in Table V. The overwhelming presence of Poor readings implies that the air quality was mostly unhealthy throughout the monitoring

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

period but did not cross the threshold of the Severe classification. Thus, the continuous reporting node proves to be useful in ensuring awareness not just during emergencies, but during the entire monitoring timeframe. The relatively small share of Severe readings, however, may still end up being the segment that offers the greatest practical benefits, as those are the instances that the buzzer/RGB-LED alert system is meant to detect.

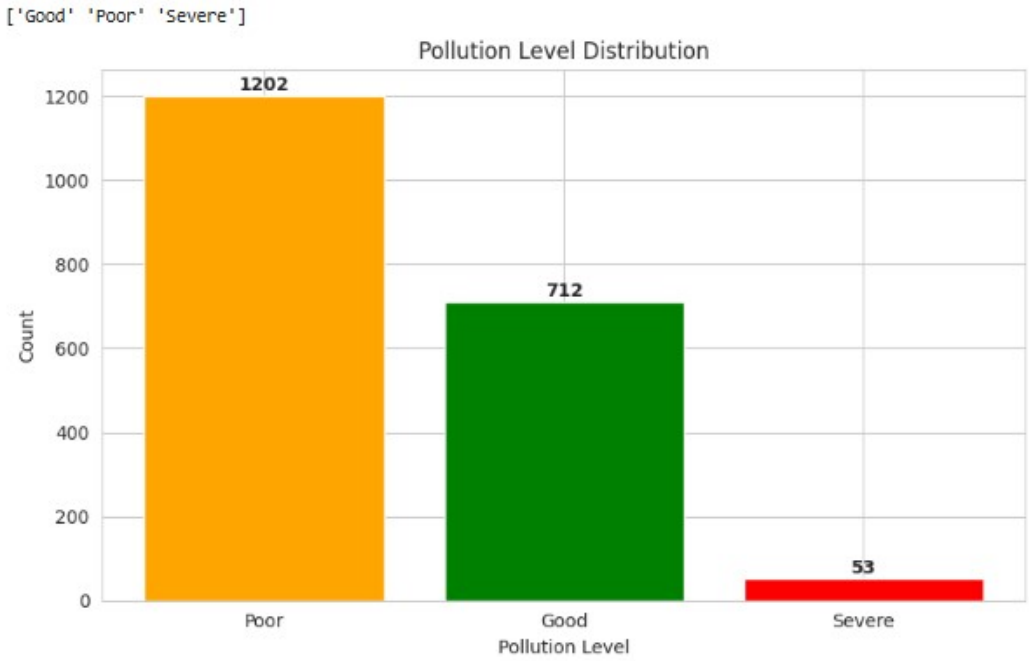


Fig. 5. Distribution of hourly readings across the Good, Poor and Severe pollution bands.

TABLE V. Pollution-Level Distribution Summary

Category	Count	Share
Poor	1202	61.1%
Good	712	36.2%
Severe	53	2.7%

E. 24-Hour AQI Forecast

In Fig. 6 the predicted AQI for 24 hours on September 1, 2026, is provided. The chart shows similar behavior to that of the diurnal pattern discussed in Section VI-C with a low level of about 75 at 8 a.m. followed by gradual climb over the period of 9:00 to 18:00 with temp AQI nearing the range of 85-133, and then sharp rise in the evening hours reaching to 174 around 8 p.m. The comparison of Fig. 4 and Fig. 6 suggests that hour of the day serves as a good predictor for this location and that lightweight forecasting model can successfully predict daily rise in pollution.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

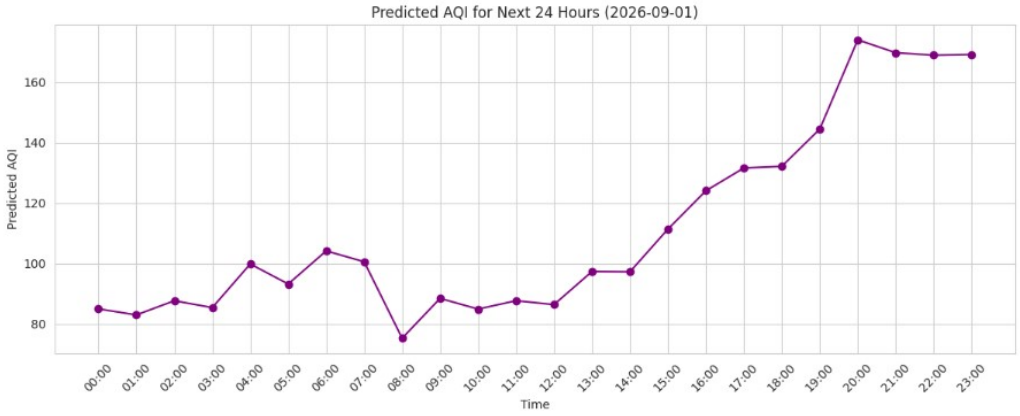


Fig. 6. Predicted AQI for the next 24 hours (1 September 2026).

F. Discussion

In summary, the results from the daily, diurnal, and forecasting have the same idea that pollution at the site doesn't just follow the daily level but that it follows a slow multi-day accumulation that it is also based on quick meteorological changes. Additionally, it shows that pollution at the site changes according to regular rhythms during the day based on traffic conditions and diurnal dynamics. Because the forecasting model relies mainly on the rhythms taking place during the day, it can predict changes in AQI levels throughout the day. Thus, while the model is able to predict patterns in AQI levels that usually take place in the evening, it cannot predict changes that are usually caused by weather as those would require original meteorological information.

VII. LIMITATIONS AND PRACTICAL CHALLENGES

There are several constraints that affect the findings mentioned above and are to be considered when planning new applications in the future. First of all, MQ135 and GP2Y1010AU0F sensors are analog devices that have not undergone calibration and are therefore cheap; however, without periodic co-location of such a type of sensors with the use of high-quality standards, the absolute AQI obtained by the sensor could change with the influence of temperature, humidity and the age of the sensor. Secondly, the parameters of the three-level Good/Poor/Severe classification used for alarm purposes are a rather significant simplification of the six-level CPCB scale designed for instantaneous decision-making, which resulted in losing some intermediate Satisfactory/Moderate/Very-Poor distinctions. Thirdly, the forecasting model relies on information from one particular node's three-week history and employs only autoregressive and hour-of-the-day characteristics; the model does not include data from other forecasting models like wind, precipitation or boundary-layer height which could help extend the period of forecasting up to three days as it is shown in Fig. 3. Finally, one-node deployment implies a localized measurement, which makes it impossible to measure pollution

VIII. CONCLUSION AND FUTURE WORK

This study has proposed an AIoT Air Quality Monitoring Network that has utilized an ESP32 microcontroller and sensors that are cost-effective in sensing gas, particulate matter and temperature/humidity. This network was employed for twenty days in order to evaluate pollution patterns and predict Air Quality Index for a short period. The study gives a daily pattern that shows an increase and

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

a decrease cycle ranging from 93 to 224 AQI. The study also proved the consistency of daytime air quality. Moreover, the data shows that 61.1% of all results are within the Poor category. The forecasting successfully replicated historical day pattern, showing the effectiveness of a low-cost customer base sensor and simple time-series model.

Future efforts will be focused in four areas. First, the single-node implementation will be upgraded to a multi-node topology in order to map pollution levels in specific locations within a city or a campus. Second, new pollution indicators such as laser PM2.5/PM10 there will be introduced in order to achieve complete compliance with the CPCB indicator list. Third, the method of calibration will be enhanced through a regular reference calibration process in order to be able to determine and eliminate the sensor drift. Finally, more complex models based on recurrent neural networks such as LSTM will be applied as new multi-node and multi-season training samples are collected.

ACKNOWLEDGMENT

The authors would like to thank Dr. Vishal Puranik, their research guide, for his guidance and support throughout this study. His helpful suggestions, encouragement, and valuable inputs helped the authors complete this research work successfully.

REFERENCES

[1] A. Ghazaryan, L. Fidanyan, and A. Kirakosyan, “AI-powered air quality prediction using IoT sensor networks: A case study from Armenia,” E3S Web Conf., vol. 725, Art. no. 03003, Jul. 2026, doi: 10.1051/e3sconf/202672503003.

[2] J. Cliffton Akoi, J. Ribi, Z. Lamat, and N. Rali, “AIoT-based indoor air quality monitoring and machine learning prediction framework for assessing ventilation risk in TVET institutions,” J. Eng. Sci. Energy Sustain., vol. 1, no. 1, pp. 1–14, Apr. 2026, doi: 10.33736/jese.12329.2026.

[3] S. Dey, R. Raina, S. Mishra, A. S. Prasad, and R. Dharavath, “GreenEdge AI: Sustainable federated learning for smart city air quality prediction,” J. Ind. Inf. Integr., vol. 50, Art. no. 101081, 2026.

[4] A. Mujianto and C. Mashuri, “Real-time air quality prediction using IoT sensor networks and LSTM deep learning model,” J. Sist. Inf. Bisnis, vol. 15, no. 4, 2026.

[5] P. Camacho-Magriñán, D. Sales-Lérida, B. Priego-Torres, and D. Sánchez-Morillo, “Monitoring and predicting indoor air quality: An IoT and machine learning-based approach,” in Proc. Int. Conf. Inf. Technol. Appl. (ICITA 2025), Lecture Notes in Networks and Systems, vol. 1889, 2026, pp. 73–82, doi: 10.1007/978-3-032-21174-3_8.

[6] J. Rosa Bilbao, F. S. Butt, D. Merkl, M. F. Wagner, J. Schäfer, and J. Boubeta-Puig, “IoT-based indoor air quality management system for intelligent education environments,” IEEE Internet Things J., 2025, doi: 10.1109/JIOT.2025.3539886.

[7] S. Varur, U. M. Hiremath, D. Hireraddi, N. Nagaral, K. Patil, and G. Vernekar, “Breath of the future: Predicting air quality index with ML and IoT,” in Proc. SCITEPRESS, 2025.

BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

[8] K. S. Pranikaa and M. Gayathri, "IoT-based ESP32 system for monitoring hazardous gases and particulate matter," in Proc. 3rd Int. Conf. Sustain. Comput. Data Commun. Syst. (ICSCDS), 2025, doi: 10.1109/ICSCDS65426.2025.11167473.

[9] K. Chatterjee et al., "Toward cleaner industries: Smart cities' impact on predictive air quality management," IEEE Access, vol. 12, 2024, doi: 10.1109/ACCESS.2024.3406502.

[10] U. R. Babu et al., "A neural network approach for predicting air quality forecasting in smart cities based on ST-LSTM technique," in Proc. Int. Conf. Intell. Algorithms Comput. Intell. Syst. (IACIS), 2024, doi: 10.1109/IACIS61494.2024.10721654.

[11] I. Gryech, C. Asaad, M. Ghogho, and A. Kobbane, "Applications of machine learning & Internet of Things for outdoor air pollution monitoring and prediction: A systematic literature review," Eng. Appl. Artif. Intell., vol. 137, 2024, arXiv: 2401.01788.

[12] S. Felici-Castell, J. Segura-Garcia, J. J. Perez-Solano, R. Fayos-Jordan, A. Soriano-Asensi, and J. M. Alcaraz-Calero, "AI-IoT low-cost pollution-monitoring sensor network to assist citizens with respiratory problems," Sensors, vol. 23, no. 23, Art. no. 9585, Dec. 2023, doi: 10.3390/s23239585.

[13] A. Samal, L. Samal, A. K. Swain, and K. Mahapatra, "Integrated IoT-based air quality monitoring and prediction system: A hybrid approach," in Proc. 9th IEEE Int. Symp. Smart Electron. Syst. (iSES), Ahmedabad, India, Dec. 2023.

[14] A. Kataria and V. Puri, "AI- and IoT-based hybrid model for air quality prediction in a smart city with network assistance," IET Netw., vol. 11, no. 6, 2022, doi: 10.1049/ntw2.12053.

[15] A. Catovic, E. Kadusic, C. Ruland, N. Zivic, and N. Hadzajlic, "Air pollution prediction and warning system using IoT and machine learning," in Proc. Int. Conf. Electr., Comput., Commun. Mechatronics Eng. (ICECCME), 2022.