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Multi Model Remote Parameter Monitoring and Detection Using ML Algorithms for Pollution Prediction System

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Abstract
Experimental work of Environmental pollution monitoring has become crucial for sustainable urban development and public health management. This paper presents a comprehensive real-time pollution monitoring system capable of simultaneously tracking multiple environmental parameters including air quality, carbon monoxide concentration, temperature, humidity, and dust. The system integrates an ESP32 microcontroller with multiple specialized sensors, GPS based geo-tagging capabilities, and cloud-based data visualization through Blynk IoT platform. A novel aspect of this work includes the implementation of machine learning algorithms for continuous predictive analytics, enabling forecasting of pollution trends based on historical data patterns. The system features local display capabilities via LCD screen and remote monitoring through IoT connectivity, making it suitable for both mobile and stationary deployment scenarios. Field deployment results demonstrate the system's effectiveness in providing accurate, real-time environmental data with predictive capabilities that can assist in proactive pollution management strategies. The compact design, powered by a regulated DC supply with buck boost conversion, ensures portability and reliability for diverse environmental monitoring applications. The proposed work employs Random Forest algorithm with neural network LSTM and provides a accuracy of R^2 as 91% from different geotagged location along with validation parameters and the obtained is superior among conventional systems.

Keywords: *Environmental monitoring, IoT, pollution detection, machine learning prediction, multi-sensor integration, ESP32, air quality monitoring, geo-tagged sensing.*

1. Introduction

One of the biggest issues affecting urban sustainability, climate stability, and public health today is environmental pollution. Real-time environmental monitoring is crucial for smart city planning and public safety because prolonged exposure to contaminated air and particulate matter raises the risk of respiratory and cardiovascular disorders [14], [15]. Apart from air pollution, noise pollution has become a significant urban issue, particularly in areas with high traffic and industrial activity [20]. Therefore, rather than depending solely on single-sensor monitoring, contemporary pollution monitoring systems must measure several parameters concurrently to provide a comprehensive environmental assessment [16], [9]. Conventional air quality monitoring systems primarily rely on laboratory-grade equipment and government-grade fixed monitoring stations. Despite offering precise data, these systems have poor spatial coverage due to their high cost, bulk, and location-specificity [13], [19]. Because of localized dust sources, industrial emissions, and traffic, pollution levels can vary greatly over short distances, making fixed stations inadequate for citywide monitoring [13], [19]. This encourages the creation of widely deployable, affordable, scalable, and portable IoT-based monitoring solutions [2], [8]. Additionally, recent studies highlight that proactive environmental management requires a shift in monitoring from reactive sensing to predictive analytics [18], [3].

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Because of their low cost and capacity to send real-time data to cloud dashboards, Internet of Things-based air quality monitoring systems have drawn a lot of interest. For instance, P. Chandra et al. used sensor integration, microcontroller-based deployment, IoT, and machine learning to demonstrate scalable urban air quality assessment [2]. In a similar vein, hybrid cloud-edge architectures have been suggested for cloud-integrated pollution monitoring systems to facilitate extensive historical analysis and forecasting [8]. According to these studies, cloud connectivity is crucial for long-term data storage and prediction in addition to remote visualization [8], [19]. Furthermore, scalable and standardized IoT monitoring frameworks are essential for the adoption of smart cities, according to international viewpoints on IoT-based air quality standards [15]. However, sensor drift, cross-sensitivity, and ambient noise limit the accuracy of the majority of inexpensive monitoring systems. Temperature and humidity fluctuations particularly impact MQ-series sensors and inexpensive gas sensors, leading to unstable readings [9], [12]. In order to improve the accuracy of pollution measurement, Thakre et al. used Kalman filtering techniques to address noise and sensor drift in MQ-series sensors [9]. Similarly, in order to increase accuracy and decrease systematic error, Garg et al. suggested deep learning-based calibration techniques for inexpensive sensors [12]. These studies show that intelligent calibration and signal processing are necessary for realistic low-cost pollution monitoring implementations [9], [12]. Modern environmental sensing systems now need to be able to predict in addition to monitor. Random Forest was found to be a very accurate technique for real-time sensing and classification of air pollution conditions by P. K. Rautaray et al. after evaluating several machine learning models [1]. For spatiotemporal air pollution forecasting in smart city settings, ensemble machine learning techniques have also shown promise [18]. By combining several predictors, Patel et al. showed that ensemble models improve forecasting performance and are therefore robust for dynamic urban datasets [18]. Monitoring systems are thus converted from reactive platforms into proactive instruments that can predict pollution trends through the integration of machine learning prediction [18], [3]. Because the distribution of pollution varies throughout a city, location-based pollution monitoring is another essential requirement. Numerous proposals have been made to identify pollution hotspots and enhance spatial resolution using GPS-guided mobile monitoring solutions [19]. Kim et al. demonstrated how cloud analytics and GPS-guided mobile environmental monitoring enhance pollution mapping and facilitate efficient geotagged analysis [19]. Similarly, in order to document actual pollution variations across various regions, Rajhans et al. suggested urban pollution mapping using mobile IoT nodes [13]. The necessity of GPS integration in portable IoT monitoring systems for hotspot mapping and detection is strongly supported by these studies [13], [19]. In order to lower latency and facilitate quicker local processing, recent developments have also looked into edge computing. Kalaivani et al. demonstrated that localized processing lowers cloud latency and enhances performance in high-density urban areas when they proposed intelligent AQI monitoring using edge computing on ESP32 [7]. Similar to this, Nguyen et al. highlighted the advantages of merging several sensor streams with edge intelligence in their proposal for edge-assisted multi-modal sensor fusion for real-time air quality assessment [16]. Tripathi et al. also emphasized how TinyML deployment on microcontrollers could be used for real-time hazard detection, allowing for on-device inference and a decrease in reliance on cloud computing [10]. According to these studies, one of the main directions for next-generation pollution monitoring systems is edge-based processing [7], [10], and [16]. Furthermore, Ramya et al. used gradient boosting and multi-agent sensor fusion to demonstrate smart air and water monitoring for industrial emissions, demonstrating that multi-parameter fusion enhances industrial effluent tracking [6]. For real-world monitoring applications, multi-sensor systems are therefore becoming more

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and more popular than single-sensor systems [6], [16]. This project suggests a Multi-Model Remote Parameter Monitoring and Detection System using Machine Learning Algorithms for Pollution Prediction in light of these requirements and research avenues. By offering a scalable, portable, and reasonably priced multi-parameter monitoring platform, the suggested system aims to address the drawbacks of current single-parameter, stationary, and reactive monitoring solutions [2], [15]. The system uses inexpensive sensors that are interfaced with an ESP32 microcontroller to continuously measure important environmental parameters like temperature, humidity, dust density, carbon monoxide concentration, noise levels, and air quality. Compared to single-sensor monitoring, multi-modal sensing increases the accuracy of environmental assessment by combining multiple parameters [16], [9]. The suggested system is in line with contemporary multi-sensor fusion techniques for accurate noise management and air quality evaluation [9], [16]. Because of its integrated Wi-Fi and suitability for edge computing applications, the ESP32 functions as the primary processing and IoT communication unit. For remote monitoring and real-time visualization, the gathered sensor data is processed locally before being sent to the Blynk IoT cloud. Large-scale historical data storage and analysis require cloud-based monitoring, as shown by cloud-integrated monitoring frameworks [8], [19]. For on-site monitoring, the suggested system additionally incorporates a local 16x2 LCD display, guaranteeing usability even in situations where internet connectivity is not available. Both stationary and mobile deployment are supported by such hybrid local remote monitoring designs, which also increase system practicality [2], [15]. Location-based pollution tracking and hotspot identification are made possible by the integration of a Neo-6M GPS module, which provides geo-tagged sensor readings. According to research on GPS-based cloud analytics, GPS-guided monitoring enhances spatial resolution and facilitates pollution mapping [19]. It has also been demonstrated that mobile IoT nodes are useful for recording location-specific pollution variations in urban settings [13]. As a result, GPS integration increases the system's suitability for field deployment and smart city monitoring [13], [19]. Targeted pollution control measures and real-world decision-making are supported by this geo-tagged monitoring capability [15], [19]. In addition to monitoring, the proposed system uses machine learning algorithms to predict and classify pollution. Random Forest is chosen for its high accuracy and reliability in real-time sensing applications, as shown in pollution monitoring studies inspired by IoT [1]. Ensemble machine learning methods have also proven effective for forecasting air pollution trends in smart cities [18]. Additionally, studies on UAV-based monitoring and prediction indicate that hybrid models like CNN-GRU can improve prediction accuracy for 3D pollution mapping, which emphasizes the value of smart forecasting methods [3]. Thus, the proposed system combines IoT monitoring with machine learning-based prediction to help with proactive environmental management [18], [3].

2. Methodology

Real-time environmental sensing, processing, geotagging, cloud communication, and predictive analytics (multimodal) are all features of the integrated embedded framework develops pollution monitoring system. Figure 1 depicts the system's general architecture, and Table 2.1 provides a summary of the specific hardware elements utilized in the implementation.

2.1. Proposed System Description

The sensing and acquisition unit, the processing unit, the communication and display unit, and the power management unit are the four main functional units that make up the system, as illustrated in Figure 1. Several environmental sensors, including the MQ-135 (air quality), MQ-07 (carbon monoxide), DHT11 (temperature and humidity), and GP2Y1014AU0F (dust sensor), are part of the sensing and acquisition unit. These sensors produce analog or digital signals in response to their continuous monitoring of environmental parameters. The analog voltage outputs from the MQ-135 and MQ-07 sensors are proportionate to the levels of gas concentration.

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Similarly, light scattering from particulate matter is the basis for the analog output of the GP2Y1014AU0F dust sensor. The DHT11 sensor, on the other hand, produces calibrated digital output that shows the values of temperature and relative humidity. The ESP32 development module serves as the central processing unit and is interfaced with all sensor outputs. The ESP32's integrated Analog-to-Digital Converter (ADC) transforms the analog signals into digital values.

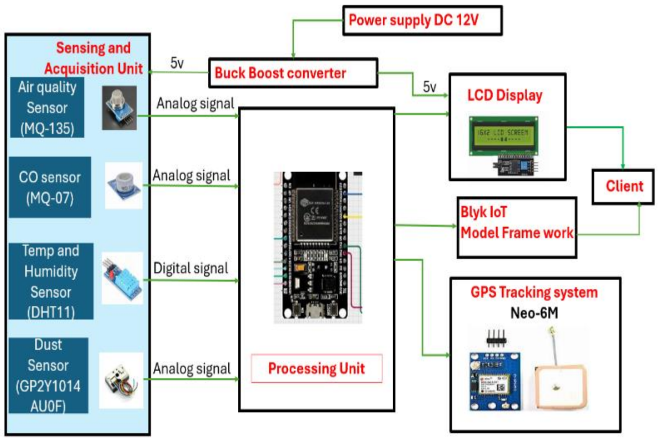

Figure 1 IoT Integrated Multimodal Pollution Monitoring Using Esp32 Microcontroller

To lower noise and increase measurement stability, the controller applies signal conditioning techniques like averaging and simple filtering. Following processing, the values are transformed into useful environmental parameters like temperature (°C), humidity (%), dust density (µg/m³), and CO concentration (ppm). A Neo-6M GPS module is incorporated into the system to allow location-aware monitoring. Real-time latitude and longitude coordinates are provided by the GPS module through serial communication with the ESP32. By appending these coordinates to every dataset, geo-tagged pollution monitoring and hotspot identification are made possible.

A 16x2 LCD (I2C interface) is attached to the ESP32 to show current environmental data for local visualization. Concurrently, the ESP32 sends the geo-tagged and processed data to the Blynk IoT cloud platform via its integrated Wi-Fi capability. Through a web or mobile dashboard, the cloud platform allows clients to monitor remotely and saves historical data for later analysis. A 12V DC supply powers the entire system. The ESP32, sensors, LCD, and GPS module all require a steady 5V output, which is provided by a buck-boost converter that controls the input voltage. Stable system operation and effective power distribution are thus guaranteed.

2.2. Hardware Components Description

The hardware parts utilized in the suggested system are listed in Table 2.1 together with information about their models and purposes. The primary controller in charge of data collection, processing, Wi-Fi communication, and system coordination is the ESP32 Development Module. While the MQ-135 sensor detects several dangerous gases to evaluate the overall quality of the air, the MQ-07 sensor is solely focused on detecting carbon monoxide. Environmental correlation analysis is made possible by the DHT11 sensor, which measures temperature and humidity. The GP2Y1014AU0F optical sensor uses the principles of infrared light scattering to detect dust.

Table 1 System Components and Specifications

Component	Model / Type	Function
ESP32	ESP32 Dev Module	Main controller
CO Sensor	MQ-07	Carbon Monoxide measurement
Air Quality Sensor	MQ135	Gas & air quality sensing
Temperature & Humidity Sensor	DHT11	Temperature & Humidity Sensing
Buck Boost Converter	Power distribution	Power Management
Dust Sensor	GP2Y1014AU0F	Dust Sensing
GPS Tracking system	Neo-6M	Geotagged location Tracking
LCD	16x2 LCD / I2C LCD	Local display

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Geotagged location tracking is made possible by the Neo-6M GPS module, which increases the system's suitability for applications involving smart cities and spatial pollution monitoring. By controlling the supply voltage, a buck-boost converter guarantees appropriate power management. Real-time local display of measured parameters is provided by the 16x2 LCD module.

3. System Architecture

1. System Overview.

This experimental work presents an integrated pollution monitoring system that addresses these limitations through several key innovations:

1. **Multi-parameter Monitoring and data Acquisition:** Simultaneous monitoring of six critical environmental factors (air quality, CO concentration, temperature, humidity, and dust)
2. **Geo-tagged data collection:** Integration of GPS module for spatial mapping of pollution hotspots.
3. **Dual monitoring interface:** Local LCD display combined with cloud-based IoT visualization.
4. **Predictive analytics:** Machine learning algorithms for forecasting future pollution trends.
5. **Portable and cost-effective design:** Optimized power management.

The system is designed as shown in Figure 2. to be deployable in various scenarios, from mobile monitoring vehicles to fixed installation sites, providing comprehensive environmental data that can inform policy decisions and public awareness initiatives.

2. Sensing unit:

1.Air Quality Monitoring: The MQ-135 gas sensor detects air pollutants including ammonia, nitrogen oxides, benzene, smoke, and CO_2, providing analogy output proportional to gas concentration.

2.Carbon Monoxide Detection: The MQ-07 sensor specifically targets carbon monoxide with high sensitivity ideal for automotive and industrial pollution monitoring.

3.Temperature and Humidity: The DHT11 digital sensor provides calibrated measurements essential for understanding pollution dispersion patterns and thermal comfort indices.

4.Dust: The GP2Y1014AU0F optical dust sensor employs infrared LED and phototransistor to detect fine particulate matter (PM2.5 and PM10).

5.Geographical Location: The Neo-6M GPS module provides precise latitude, longitude, and timestamp data for spatial mapping.

Table 2 Blynk IoT Virtual Pin Mapping and Data Summary

Pin	Parameter	Unit	Range
V0	Air Quality	0 – 100	0 = Clean
V1	CO Level	0 – 100	0 – 2000 ppm
V2	Humidity	%	20 – 90%
V3	Temperature	°C	0 – 50°C
V4	Alert Message	String	Text
V5	Dust Density	µg/m³	0 – 500
V6	GPS Location	String	URL
V7	Enable Send	0 / 1	Toggle

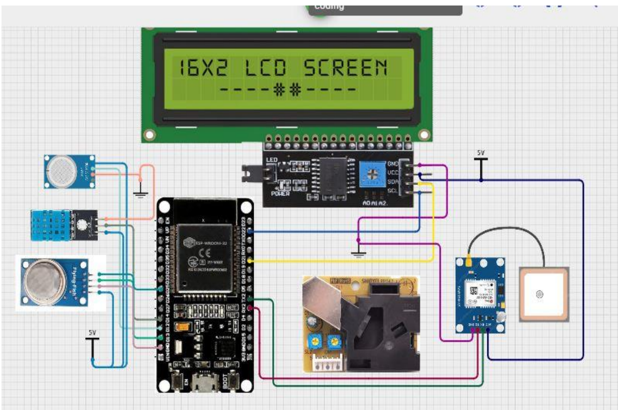

Figure 2 System Architecture

The Blynk IoT platform's virtual pin mapping for real-time environmental monitoring and control is shown in Table 2. The Blynk dashboard and the

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microcontroller (ESP32/NodeMCU) in this system can communicate thanks to software-defined channels called virtual pins V0 through V7. For environmental condition monitoring, V0 and V3 transmit humidity (20–90%) and temperature (0–50°C), respectively; V1 corresponds to CO level measurement (0–2000 ppm) displayed in a 0–100 scaled format; and V0 represents air quality with values scaled from 0–100, where 0 indicates clean air. When any parameter surpasses predetermined thresholds, alert messages are sent via V4, which is set up as a string-type pin. To track particulate pollution, V5 stands for Dust Density, which is measured in µg/m³ between 0 and 500. While V7 serves as a binary toggle (0/1) to enable or disable data transmission or alert notifications, V6 transmits GPS location data in URL format for real-time tracking. Within the overall system architecture, this structured virtual pin allocation guarantees organized data acquisition, visualization, remote monitoring, and control.

3. Processing and Control Unit:

The ESP32 microcontroller serves as the central processing unit, offering dual-core 32-bit processor operating at 240 MHz, integrated Wi-Fi connectivity, 12-bit ADC channels, and low power consumption. The ESP32 continuously polls sensor data, performs validation and formatting, manages local display output, and transmits data to the cloud platform.

4. Display Subsystem:

The JHD 162A LCD display (16×2-character display) provides immediate local visualization of sensor readings, crucial for field verification, standalone operation, and Realtime feedback in mobile monitoring scenarios.

5. Power Management:

The power subsystem employs a Switch Mode Power Supply (SMPS) adapter converting AC mains to regulated 12V DC, followed by an XL6009 DC-DC buck-boost converter transforming the supply to 5V operating voltage with greater than 90% efficiency. A custom PCB houses the power converter, LCD connections, and power jack.

4. Software Implementation

1. Embedded Firmware:

The ESP32 firmware implements continuous sensor polling with moving average filters, data conversion to engineering units, threshold checking and alerts, and JSON data packaging for transmission. Communication protocols include Wi-Fi management with automatic reconnection and MQTT implementation for Blynk IoT platform.

2. IoT Platform Integration:

Blynk IoT platform provides real-time dashboards with graphical widgets, persistent time-series data storage, remote configuration capabilities, and automated threshold-based alerts.

C. Machine Learning for Predictive Analytics: Multiple algorithms have been evaluated including Linear Regression (baseline), Random Forest (ensemble method), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) Networks specialized for time-series prediction. The dataset employs 80% training and 20% testing split with cross-validation for hyperparameter tuning.

Table 3 ML Model Performance Metrics Comparison.

Model	Prediction Horizon	R^2 Score	RMSE (µg/m³)	MAE (µg/m³)	Training Time
Linear Regression	1-hour	0.65	32.1	24.5	< 1 min
Random Forest	1-hour	0.82	18.3	14.2	~15 min
SVR	1-hour	0.79	21.4	16.5	~10 min
LSTM (Proposed)	1-hour	0.91	12.3	8.7	~1.5 hrs
LSTM (Proposed)	24-hour	0.76	24.6	18.2	~1.5 hrs

The performance of the applied machine learning algorithms for pollution prediction is contrasted in

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Table 3. This study employed a Neural Network model (LSTM) and Random Forest for predictive analysis. With a moderate RMSE (18.3 µg/m³) and MAE (14.2 µg/m³), Random Forest demonstrated good performance with a relatively short training time (~15 minutes), achieving an R2 score of 0.82 for 1-hour prediction. All other models performed worse than the suggested LSTM model, which was created to capture temporal dependencies in environmental data. With a significantly lower RMSE (12.3 µg/m³) and MAE (8.7 µg/m³), it obtained the highest R2 score of 0.91 for 1-hour forecasting. Despite the increased complexity, LSTM maintained stable performance for extended 24-hour prediction, with an R2 of 0.76. The LSTM was chosen for dependable time-series pollution forecasting in the suggested system due to its higher accuracy and lower error metrics, despite the fact that it required a longer training period (about 1.5 hours).

Results and Discussion

5.1. Results

The proposed multi model environmental pollution monitoring system performed reliably and accurately in real-time field settings. The ESP32-based module reliably sensed temperature, humidity, dust density, CO concentration, and air quality all at once. GPS allowed location-based pollution tracking, and sensor data was sent to the Blynk cloud for minimally latency real-time visualization, logging, and remote access. Stable and portable operation was guaranteed by the controlled DC supply with buck-boost conversion and local LCD display. Reliability over traditional systems was confirmed by the Random forest based predictive model's R^2 = 0.91% forecasting accuracy, which was validated using standard error metrics. The real-time monitoring dashboard with geotagged pollution intensity mapping and real-time sensor readings is shown in Figure 3. The system classified the environment as Low Pollution during testing with readings of AQI = 65, CO = 0 ppm, humidity = 54%, temperature = 26°C, and dust density = 0 µg/m³. Accurate spatial mapping and smooth IoT synchronization are confirmed by the GPS-based visualization.

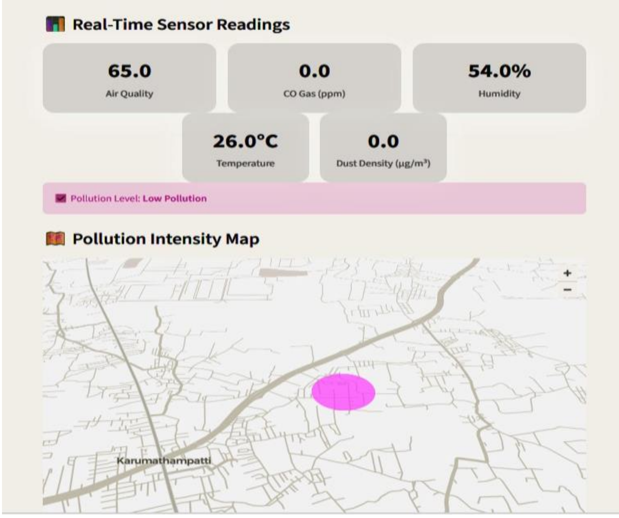

Figure 3 Simulation Result Showing Pollution Identified in Geo Tagged Locations.

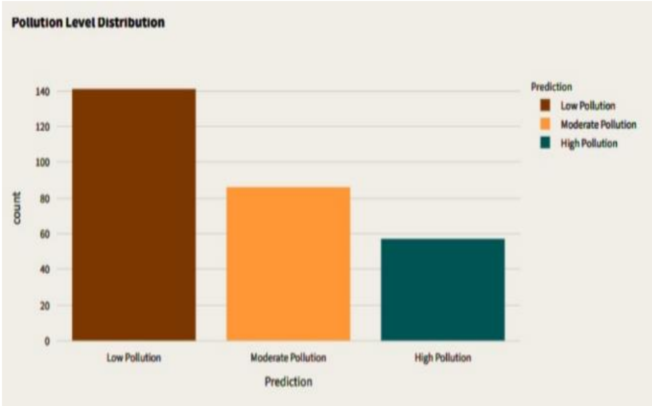

Figure 4 Analytical Evaluation of Pollution Levels

The figure 4 depicts the pollution levels produced by the suggested monitoring system is shown in the figure. Low pollution, moderate pollution, and high pollution are the three categories into which the bar graph divides environmental conditions. In contrast to the other two levels, it is found that the Low Pollution category predominates, while Moderate Pollution manifests at a medium level and High Pollution occurs relatively infrequently. This distribution shows how well the system uses threshold-based prediction logic and real-time sensor inputs to classify environmental conditions. The dependability of the applied model in identifying different pollution intensities under various environmental conditions is demonstrated by the distinct categories.

5.2. Discussion

In terms of prediction accuracy, monitored parameters, cost, and control strategy, Table 4 compares the suggested system with current pollution monitoring techniques. Simple single-sensor systems that monitor only one or two parameters at low cost and have poor prediction accuracy (R2 = 0.65–0.72) are dependent on static or manual control mechanisms.

Table 4: Performance Comparison with Existing Systems

Method	Avg. Prediction Accuracy (R^2)	Parameters Monitored	Cost (USD)	Control Type
Single Sensor (Basic)	0.65 – 0.72	1 – 2	\$30 – \$50	Manual / Static
Commercial System	0.88 – 0.92	2 – 4	\$500 – \$800	Automated / Fixed
Garg et al. [12]	0.88 – 0.92	1 – 2	\$80 – \$150	DL Calibration
Rajhans et al. [13]	N/A (MAE=18.2)	3	\$150/node	Mobile Only
Proposed System	0.91 (1-hr)	6 + GPS	\$120	Adaptive / Smart

Commercial systems monitor up to four parameters and have a higher accuracy (0.88–0.92), but they are much more expensive (\$500–800) and have fixed automation. Similar accuracy was attained by the Garg et al. system, although it only supports a small number of parameters with deep learning calibration. Similarly, Rajhans et al. reported MAE = 18.2 without R2 evaluation, concentrating on mobile monitoring.

Conclusion

In this proposed approach, an ESP32 microcontroller, inexpensive environmental sensors, GPS geotagging, IoT cloud connectivity, and machine learning integration were used to successfully develop a real-time multi-parameter pollution monitoring and prediction system. Through the Blynk IoT platform, the system provides both local display and remote visualization for important parameters like temperature, humidity, dust concentration, carbon monoxide, noise levels, and air quality. While the machine learning model supports pollution level classification and future trend prediction for proactive monitoring, the GPS integration allows location-based pollution tracking and hotspot identification. All things considered, the suggested solution is scalable, affordable, and portable, making it appropriate for industrial monitoring, smart city implementation, and environmental sensing applications focused on public health.

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