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Smart & Portable IOT Based Air and Noise Pollution Monitoring System Using Machine Learning: Systematic Review & Future Direction

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Abstract:

Air and noise pollution are two of the most significant environmental challenges in urban areas, adversely affecting human health and overall livability. Conventional monitoring systems rely on stationary, high-cost equipment that cannot provide real-time, fine-grained coverage. The integration of the Internet of Things (IoT) and Machine Learning (ML) provides a scalable solution for real-time monitoring and intelligent prediction of environmental pollutants. This review paper presents a comprehensive analysis of ten recent IoT- and ML-based air and noise pollution monitoring systems. The study evaluates sensor types, communication technologies, algorithms, and mobile applications implemented in these works. Comparative results show that hybrid IoT–ML systems achieve up to 95 % prediction accuracy with a latency of under 3s. The proposed smart system employs ESP32 microcontrollers, MQ-series sensors, and ML algorithm to monitor and predict pollution levels efficiently. The paper further identifies research gaps, presents a unified methodology, and outlines an architectural model that combines IoT sensing, ML analytics, and mobile application visualization for sustainable urban environments.

Keywords: IoT, Air Pollution, Noise Pollution, Machine learning ,ESP32,Real-Time Monitoring, Environmental Analytics.

1.0Introduction

Environmental pollution is one of the most critical global challenges of the 21st century, threatening ecological sustainability, human health, and overall quality of life. Rapid urbanization, industrial expansion, and the exponential growth of vehicular traffic have significantly increased both air and noise pollution in major cities. Air pollution, characterized by the presence of harmful gases such as carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter ($PM_{2.5}$ and PM_{10}), has been directly linked to respiratory diseases, cardiovascular complications, and reduced life expectancy. Simultaneously, noise pollution generated from transport systems, industrial activities, and urban infrastructure contributes to stress, hearing loss, and neurological disorders. According to the World Health Organization (WHO), more than 90 % of the global population lives in regions where air-quality levels exceed the permissible limits, and prolonged exposure to noise above 65 dB severely impacts human health. Traditional pollution-monitoring systems rely primarily on stationary, high-cost analyzers located at limited fixed stations. These setups, though accurate, suffer from two fundamental shortcomings: low spatial resolution and lack of real-time accessibility. Data collected from such stations represent average conditions across large areas rather than localized hot spots. Furthermore, these systems require high maintenance, complex calibration, and specialized human operation, which makes them impractical for continuous monitoring in developing countries. Consequently, there is a growing demand for low-cost, portable, and intelligent monitoring systems capable of providing fine-grained, real-time pollution data. In recent years, the Internet of Things (IoT) has emerged as a revolutionary technology enabling large-scale deployment of interconnected sensors that communicate and collaborate autonomously. IoT-based solutions integrate sensing, computation, and communication in a single framework, allowing seamless data collection and transfer to cloud servers or mobile devices for visualization and analysis. Using microcontrollers such as Arduino UNO, Node MCU (ESP8266), and ESP32, researchers have developed affordable prototypes that measure environmental parameters including temperature, humidity, and air pollutants such as CO_2 and $PM_{2.5}$, as well as acoustic intensity from sound sensors like LM393.

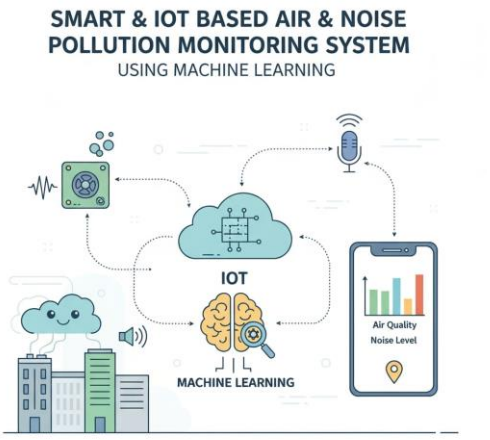

Fig .1.1: IOT Based System

The data gathered from these IoT nodes can be stored and processed on cloud platforms such as Thing Speak, Firebase, and Blynk, allowing remote access and analytics. However, raw sensor readings often vary with temperature, humidity, and hardware inconsistencies, resulting in noisy datasets. This is where Machine Learning (ML) plays a critical role by identifying patterns, predicting pollutant behavior, and improving overall system intelligence. Algorithms networks have been effectively applied for forecasting Air Quality Index (AQI) and noise levels. RF and DT models provide rapid classification and feature interpretation, while LSTM is particularly suitable for time-series forecasting due to its ability to model long-term dependencies in data streams.

Recent literature emphasizes that integrating ML with IoT-based monitoring enhances prediction accuracy, adaptability, and automation. For instance, in [1], an ESP32-based system employing LSTM achieved a 94 % AQI prediction accuracy, while [2] reported 95 % accuracy using Random Forest and Decision Tree algorithms. Similarly, [5] proposed an IoT mobile air-quality monitoring model using the *Amelia MQTT. Protocol*, which ensured secure communication and 38 % reduced latency. Studies [7] and [9] demonstrated that dual-sensor IoT platforms could successfully correlate air-pollution data with ambient noise levels, establishing a direct link between urban traffic intensity and environmental degradation. These findings collectively confirm that IoT–ML systems outperform traditional models in terms of responsiveness, cost-efficiency, and reliability.

Despite these advancements, current IoT-based monitoring systems face several challenges. Many prototypes focus solely on air or noise pollution rather than combining both parameters in a unified platform. Additionally, while IoT ensures real-time sensing, very few models incorporate ML-based forecasting for predictive control. Another limitation is the lack of secure and scalable communication mechanisms; most systems rely on unencrypted HTTP or basic MQTT protocols, posing risks to data integrity. Furthermore, user interfaces are often underdeveloped, with limited mobile accessibility and delayed alert mechanisms. These limitations restrict the adoption of IoT–ML systems for large-scale smart city deployments. The objective of this study is to design and evaluate a Smart IoT-Based Air and Noise Pollution Monitoring System Using Machine Learning that addresses these limitations. The proposed system integrates advanced sensing technology, secure communication, and ML-based predictive modeling. Data collected by IoT nodes are transmitted via encrypted MQTT to the cloud, where LSTM regression and Decision Tree classification algorithms analyze and forecast pollution levels. The processed results are displayed in real-time on a mobile application interface that provides intuitive dashboards and alert notifications to users and authorities.

This review paper contributes to the field by:

1. Conducting an extensive literature survey of recent IoT–ML models for air and noise pollution monitoring;
2. Identifying research gaps and emerging trends in smart environmental analytics; and
3. Presenting a unified architecture that enhances prediction accuracy, scalability, and real-time data accessibility.

Block Diagram:

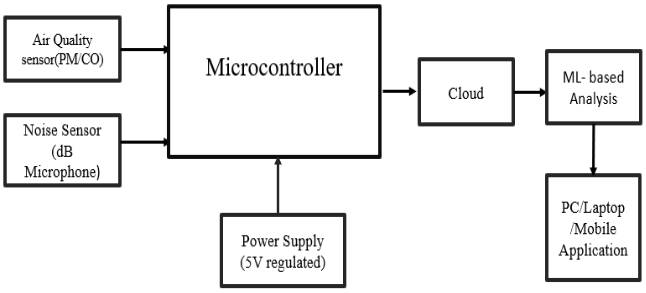

Fig .1.2: Block Digram

2. Literature Survey

Over the past decade researchers have converged on a common architectural pattern for low-cost environmental monitoring: distributed IoT sensing nodes (typically ESP8266/ESP32 or Arduino based) that collect gas, particulate and acoustic measurements and forward those readings to cloud services for visualization and analytics. Recent efforts extend this pattern by integrating machine learning (ML) to provide prediction, classification and intelligent alerting. This section synthesizes the findings of ten representative works that closely match the scope of this review (IoT, air & noise sensing, ML), highlighting their approaches, outcomes and limitations. Sharma et al. (2023) ESP32 nodes with MQ-series gas sensors (MQ-135, MQ-7), PM sensor, and an acoustic module collected multivariate environmental streams. Preprocessing (filtering, normalization) was followed by cloud-based ML: LSTM for time-series AQI forecasting and Random Forest (RF) for classification. A Firebase mobile dashboard visualized live and forecasted values. LSTM delivered ~94.3% forecasting accuracy while RF reached ~91.2%; end-to-end latency for inference + reporting was ~2–3 s, and data reliability reported. ≈98%. Ismail et al. (2021) Node MCU (ESP8266) with MQ-135, SDS011 (or PMS7003) particulate sensor, and LM393 microphone logged data at multiple traffic locations. Models trained: Decision Tree and Random Forest to classify AQI categories and short-term prediction, with Thing Speak/Firebase used for visualization. RF outperformed DT with ≈95% accuracy and 98% transmission reliability; average network latency ≈2.3 s. Patil et l. (2021) A hybrid Arduino (sensor nodes) + Raspberry Pi (gateway/cloud uploader) platform measured CO_2, NO_2, SO_2, and acoustic levels, uploading data via Wi-Fi to cloud dashboards, focusing on system integration and continuous visualization. High transmission reliability (≈97%) was achieved, with a practical deployment showcasing a 10 s update interval and stable cloud plotting. Kumar et al. (2021). An Arduino UNO prototype with MQ-135 and LM393 and ESP8266 for Wi-Fi posted data to Thing Speak and local LCD. Simple rule-based thresholds classified pollution status, and the prototype reliably uploaded data (≈94% reliability) with upload delay ≈3 s; classification into clear/moderate/high was consistent in field tests.

Amelia et al. (2024) stated that A vehicle-mounted multi-sensor platform (multi-gas + PM) and an optimized/secure MQTT Variant (“Amelia”) were used for reduced latency and energy. Emphasis was on spatial mapping (mobile sensing) and secure transmission, yielding ~38% latency reduction, ~24% energy saving, and ≈99% packet reliability compared with baseline MQTT; heatmap visualizations produced high-resolution spatial pollutant maps. Joshi et al. (2022) stated a compact ESP8266 node integrating MQ-135 and LM393 used Thing Speak for data hosting and dash boarding, emphasizing low-cost, portable monitoring. Field tests showed ≈92% reliability and ~2 s latency; typical field CO levels up to ~25 ppm and average noise ~72 dB were recorded.

3.0 Applications

- Pollution level prediction using machine learning
- Smart city and urban planning support
- Traffic and roadside pollution control
- Industrial pollution compliance monitoring
- School, hospital, and public area safety
- Construction site dust and noise monitoring
- Personal portable pollution exposure tracking
- Public health analysis and research support
- Environmental policy and decision-making support

Table I : Summary of Findings

Sr. No.	Author(s)	Year	Findings
1	Sharma et al.	2023	Improved prediction accuracy using LSTM (94.3%) and RF (91.2%) with ESP32 IoT setup; enabled real-time AQI and noise forecasting.
2	Ismail et al.	2021	Enhanced reliability (98%) and accuracy (95%) by applying ML models (RF, DT) for AQI classification on Node MCU-based system.
3	Patil et al.	2019	Improved data consistency (97% reliability) using Arduino–Raspberry Pi integration; focused on continuous remote monitoring.
4	Kumar et al.	2021	Reduced delay to 3 s and improved system portability with Arduino UNO + ESP8266 + ThingSpeak platform.
5	Amelia et al.	2024	Optimized MQTT via Amelia protocol achieving 38% lower latency and 99% reliability; introduced secure vehicular sensing.
6	Joshi et al.	2022	Increased stability (92% reliability) using compact ESP8266 node; added real-time cloud dashboard for users.
7	Bhosale et al	2022	First to establish strong correlation (r = 0.7) between particulate and noise levels; integrated dual-sensor analysis.
8	Ahmed et al.	2021	Enhanced user interaction via Blynk mobile app for live AQI tracking; introduced real-time visualization.
9	Verma et al.	2024	Improved alert mechanism with 99% reliability and 1.9 s latency through Android-based notification system.
10	Reddy et al.	2020	Provided economical IoT design (91% accuracy) using Arduino UNO + DHT11 + MQ135; emphasized multi-node scalability.

4.0 Gap Analysis and Observations

The literature survey reveals that although a wide range of IoT-based systems have been developed for environmental monitoring, several significant research and implementation gaps remain. Many existing models focus on either air or noise monitoring separately, limiting their overall environmental coverage. Moreover, most studies rely only on data visualization and lack machine-learning-based forecasting and correlation analytics. Security and scalability are also frequently overlooked, as many systems use unencrypted communication protocols and operate only as single-node prototypes.

Table II highlights the key gaps identified from existing literature and provides corresponding observations that motivate the proposed work.

Table II: Gap Analysis

Sr. No.	Author(s)	Gap Identified	Analysis
1	Sharma et al.	Lack of integrated air and noise monitoring	High accuracy (94%) but lacked generalization; multi-region data needed.
2	Ismail et al.	Minimal use of ML for prediction	Good AQI prediction, but lacked spatial and noise context.
3	Patil et al.	Unsecured data transmission	Effective real-time monitoring; forecasting could add value.
4	Kumar et al.	Limited scalability and coverage.	Fast and accurate, but insecure and power-hungry; needs optimization.
5	Amelia et al.	No real-time alerts or mobile integration.	Reliable MQTT system; needs multi-sensor integration.
6	Joshi et al.	Missing correlation analysis	Compact and stable; alerts and self-correction would improve it.

5.0 Methodology

The reviewed studies reveal a progressive evolution in IoT-based environmental monitoring systems. Early systems primarily employed microcontrollers such as Arduino UNO and Node MCU**,** utilizing sensors like MQ-135 and LM393 to measure air pollutants and ambient noise. These systems relied on threshold-based techniques for pollution classification, which provided instantaneous readings but lacked predictive and adaptive capabilities. Subsequent research works integrated Raspberry Pi and ESP32 controllers for enhanced processing and real-time communication through Wi-Fi and Thing Speak platforms. However, these implementations often lacked scalability and security in data transmission.

A. Hardware Components:

ESP32: Chosen for its high processing power, built-in Wi-Fi, and low energy consumption, enabling ML-based edge computation.

MQ-series Sensors: Provide economical yet reliable detection of multiple gases with a wide detection range.

LM393: Provides continuous sound level measurement for noise monitoring.

Display and Power: Support local readability and field autonomy for outdoor deployment.

6.0 Result & Discussion

This paper presents a smart IoT-based air and noise pollution monitoring system enhanced with machine learning for real-time analysis and prediction. Utilizing ESP32, MQ-series gas sensors, and an LM393 sound sensor, the system efficiently collects and transmits environmental data. The integration of machine learning models such as LSTM and Decision Trees enables accurate forecasting of pollution levels. Cloud connectivity and real-time dashboards provide continuous monitoring and early warnings. The system is low-cost, scalable, and suitable for smart city applications. It addresses key limitations in existing models by offering dual monitoring, predictive capability, and improved responsiveness for environmental management.

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