IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, June 2026
Impact Factor: 8.2

IoT-Enabled Hybrid ML System for Real-Time Air and Noise Pollution Monitoring

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Abstract: *Air and noise pollution has made human health and ecosystems hard, making real-time monitoring crucial for building healthier cities. Our Weather Pollution System brings an affordable IoT solution that turns raw sensor data into clear insights using smart hybrid machine learning.*
We detect air pollutants like CO, CO_2, NH_3, smoke with MQ135, MQ7, MQ2 gas sensors and use MAX9814 microphone for detection of noise levels, Where these are connected to a low-cost ESP32 board. Live Data flows into ThingSpeak cloud, where Decision Tree, Random Forest, and Multilayer Perceptron (MLP) algorithms are performed on the data to classify pollution simply as Good, Moderate, or Poor, even when IoT sensors get messy with real-world noise.
MLP consistently beats the other models on accuracy, precision, recall, and F1-score, processing fast enough for live alerts. It excels at finding patterns across multiple sensors that simple models miss.
The main work will happen in our web dashboard which will records live readings, smooth trend charts, and gives alerts making complex data simple for city officials, school administrators, or any concerned citizen. This System is Cheap to build, Easy to deploy anywhere, our system shifts pollution monitoring from expensive government stations to community-powered environmental awareness that actually drives cleaner air and calm streets..

Keywords: Environmental Pollution , Deep Learning, IoT Environment, Air Quality Index (AQI) , Noise Pollution, Hybrid Machine Learning, Real-Time Dashboards

I. INTRODUCTION

Environmental pollution is one of the most crucial topics. Besides deteriorated air quality, noise pollution is among the major environmental issues resulting from the ongoing industriousness and urbanization. Besides threatening nature, pollution is killing people and making it a problem that cannot be only localized to the environment. That is why monitoring has become a high priority for governments, NGOs, and researchers worldwide, as a measure to control pollution. The leading source of environmental pollution and therefore a big problem is air pollution. Growing numbers of vehicles, industries, and power plants running on fossil fuels have led to an increase of particulate matter and harmful gases in the air. The main air pollutants used for air quality monitoring are PM2. 5, CO2 (carbondioxide), and CO (carbon monoxide). In fact, since respiratory and airborne diseases are linked to low air quality, such monitoring is crucial for public health. Thanks to sophisticated sensor technology and real-time monitoring networks, air pollution can be observed at any time, which will therefore be vital for developing plans to make cities healthier. On Other hand noise pollution is yet another major issue that calls for our utmost attention. Noise pollution, predominantly brought about by traffic, factories, and building work, disrupts one's sleep, raises stress hormones, and even causes illnesses such as hearing disorders. According to WHO, noise above 55 dB is a serious health risk that affects millions of people living in megacities where noise levels often go up to 70-85 dB during rush hours.
To track pollution levels, the implementation of technologies has been considered. Through big data analytics, remote sensing utilizing satellite imagery, and IoT devices have been contributing to more accurate and wide-ranging data monitoring. At present, noise and air quality levels can be monitored instantly through sensors installed in cities as well as villages. Usage of deep learning and machine learning models is leading to a more comprehensive understanding of

pollution levels, methods of locating pollutant sources, and ways to estimate the impacts of pollution reduction measures. Besides making monitoring highly accurate, these technological innovations have also made it cheap and globally accessible.

Weather pollution monitoring, in our opinion, should not be done through a stationary measuring instrument, but with a system that can move with the person and together with people can serve as a network of sensors and measure people's exposure to pollution. We have developed a system which is based on the IoT concepts and at the same time has a very affordable price. The core of the system is the ESP32 microcontroller and the decision regarding the pollution level is made on the basis of machine learning models working in hybrid mode. Gas sensors used are MQ-135, MQ7, and MQ-2 together with a MAX9814 microphone sensor. In this way, the system measures the environmental parameters: CO CO2 NH3, level of smoke, and the audio noise level in decibels. Live data is being sent continuously to the ThingSpeak cloud, where the data visualization and time series analysis is done in real-time via the Decision Tree, Random Forest, and Multilayer Perceptron (MLP) models that categorize the pollution levels into Good, Moderate, or Poor.

When we combine low-cost sensors, cloud, and intelligent AI into a single system, we transform the raw environmental data that indicates pollution into actionable alerts that can actually save lives. For example, when air pollution levels go up, traffic officers can be dispatched to help alleviate traffic congestion. Also, schools can make informed decisions about outdoor activities for children, and families get notified in time to stay indoors during high pollution days. This kind of technology goes beyond just monitoring; it gives local residents up-to-date information that can help them to get more fresh air and lead a better life.

II. EXISTING MODELS

Despite increasing public awareness about environmental pollution, most existing monitoring systems still face several limitations that reduce their effectiveness in real-world urban settings. In most cases, they are not capable of providing real-time or easily accessible information. This latency very often leads to a situation when citizens, public health specialists, and emergency teams cannot act immediately in case pollution levels go up rapidly or dangerous conditions are experienced. Accurate instrument-grade monitoring devices like gas analyzers, particulate matter counters, and sound level meters that are calibrated to a high level of precision come at a high cost when buying, installing, and maintaining them. Besides regular calibration and servicing, which require a high level of technical expertise, a wide deployment of these instruments is also expensive and challenging. Such factors have led to most cities having a very limited spatial coverage and are not continuously monitored.

Noise pollution especially still remains ignored. While air quality is a major focus at the moment, the negative impacts of noise such as hearing impairment stress heart diseases, or sleep disturbance are in most cases not taken into consideration. Live noise level reports are hardly ever accessible to local government or public, which means that this grave health hazard is being ignored most of the time. Also, these days, most of the setups are only capable of simple data collection and giving alerts when limit values are exceeded. They do not have the features of assessing how serious the pollution is, can't find the areas with the most pollution, or predict the future changes. If there is no sophisticated analysis, pure sensor data can't be turned into valuable and actionable insights for the proactive pollution control.

Sometimes even when data are gathered, it is still presented in the form of computer codes that most of us don't understand. Without the use of visualization tools that are simple and easy to grasp, local residents, schools, and authorities face a huge challenge in interpreting the data and taking timely preventive measures; e. g. changing travel routes or not permitting outdoor activities during pollution peak hours. Most of all, most of the time the existing setups function as isolated systems and still have not integrated the state-of-art technologies such as the Internet of Things (IoT), cloud computing, and artificial intelligence. This lack of technology limits automation, real-time data sharing, scalability, and the creation of intelligent predictive features - all of which are elements of an efficient, urban environmental monitoring solution that is ready for the future.

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III. SYSTEM DESIGN

Sometimes, even if we get the data, they remain in the form of computer codes that most of us don't even understand. Without the use of simple and easy-to-understand data visualization tools, local residents, schools, and authorities face a great difficulty in interpreting the data and taking during pollution peak hours. Most of all, existing setups most of the time operate as isolated systems and have not even integrated modern technologies like Internet of Things (IoT), cloud computing, and artificial intelligence. This dearth of technology constrains automation, real-time data sharing, scalability, and the generation of intelligent predictive features - all of which are components of an effective, urban environmental monitoring solution that is future-ready.

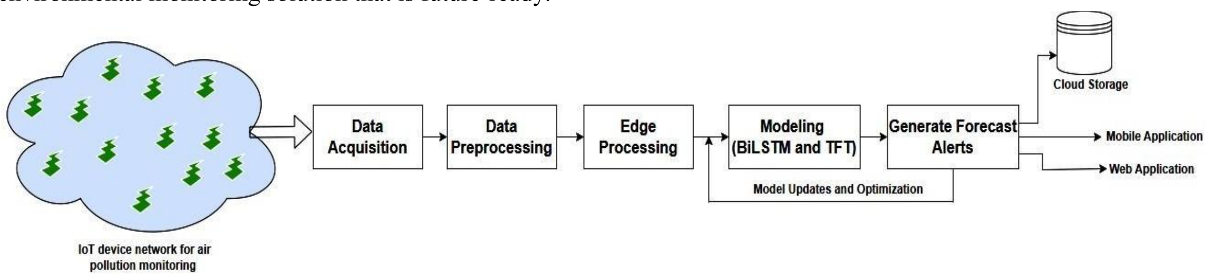

Fig 1. Overview of the proposed environmental monitoring system.

The system is structured as a multi-layered IoT framework that integrates live environmental sensing, a cloud data storage, hybrid machine learning and deep learning analysis, and a user-friendly web interface to create a pollution monitoring platform that can be scaled. At the hard ware level, ESP32 microcontroller acts as the main processing unit. It interfaces with MQ135, MQ7, and MQ2 gas sensors to detect main air pollutants, such as carbon monoxide (CO), carbon dioxide (CO), and smoke. Besides that, a MAX9814 microphone module is deployed for recording noise levels in decibels (dB), thus facilitating the continuous monitoring of air and noise pollution by one device. The sensor nodes are located at traffic intersections, residential zones, and educational institution campuses. Each node has a portable power source and is set to take measurements at regular five-minute intervals to keep data collection consistent and continuous during the entire monitoring period.

Data quality is improved early on by cleaning and transforming raw sensor inputs before they reach the cloud. Sensor readings from MQ135, MQ7, MQ2, and MAX9814 are matched using timestamps to build a single time-series stream, sent over Wi-Fi to ThingSpeak where they're saved in organized CSV files. Outliers are found with Z-score checks and IQR methods so models don't get thrown off by noise. The final data sits in a time-series tuned cloud system that lets teams pull reports fast and spot patterns across many locations and years. Usually, this setup works smoothly even when conditions shift or devices drift. Sometimes delays happen at peak usage, The system still holds up under normal load.

Decision Tree, Random Forest, and multilayer Perceptron (MLP). The modeling and analysis layer forms the core intelligence of the system. It employs a hybrid approach combining classical machine learning Deep learning techniques to classify and predict pollution levels based on the processed sensor data. Decision Tree offers clear, step-by-step splits in the sensor feature space, and it helps explain results - perfect for reports or public outreach. Random Forest stacks several trees trained on mixed data slices so outcomes stay stable even when readings jump around or get noisy. That said, the multilayer Perceptron handles messy patterns across sensors with ease thanks to its ReLU activations and softmax output. As it happens, this deep network picks up details simpler models miss, mainly during sudden shifts in air quality. Still, it doesn't show how decisions were made like the tree-based options do.Time-based features pulled from timestamps help shape the model's understanding of patterns

Normalized real-time data from MQ135, MQ7, plus mQ2, and MAX9814 sensors feed into the system, scaled using Min-Max to keep numbers consistent across devices. That standardization helps stabilize how the model learns, In particular when sensor signals get shaky. The labels for air and noise pollution. AQI Bucket and NQI Bucket, are split into three tiers: Good, Moderate, or poor. Training runs on an Adam optimizer so the network settles quickly and works

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well even with messy IoT inputs. Final results include pollution buckets plus confidence levels, letting users track quality instantly and trigger alerts automatically without needing manual checks.

The system gives users immediate results without reloading pages, thanks to a flask backend that connects prediction models to the interface. RESTful endpoints let sensors send data directly to the cloud and pull visual info back fast, reducing lag between device signals and dashboard updates. Frontend design uses HTML, CSS, and JavaScript to keep visuals smooth and up-to date. One section tracks air pollution from MQ sensors, showing AQI scores and labels in real time. Another reads MAX9814 noise levels, displaying decibel values with quality classifications. Really, both panels respond instantly, no waiting needed for city planners, school staff, scientists, and decision-makers relying on live environmental data. For now, this setup keeps operations flowing without delays or friction.

IV. RESULTS

In crowded city intersections, sensors sat 1. 5 meters above ground - just where people usually stand - to catch real-life activity. Suburban streets and school grounds followed the same setup, giving coverage across different daily rhythms. Devices warmed up before launch using standard test samples so they didn't drift off track. Every five minutes, readings rolled in for two weeks straight, filling up a detailed timeline. Early morning traffic jams showed up clearly with calm late-night drops. The data covered all points in between, from noisy commutes to quiet afternoons.

The sensors gathered unprocessed data from various weather conditions. Oxygen in air, carbon monoxide and carbon dioxide levels, smoke concentration and noise levels around were taken automatically with time stamps using technology and sent to the ThingSpeak cloud platform. Table 1 displays a sample of the readings taken during one typical monitoring session, which also recorded CO levels reaching a maximum of 3473 ppm during traffic peak hours and showed the impact of vehicle emissions on urban air quality quite clearly.

Timestamp	CO (ppm)	CO_2 (ppm)	Smoke (ppm)	Noise (dB)
2025-10-18 08:15	3473	3662	171	65
2025-10-18 08:20	3450	3690	168	63
2025-10-18 08:25	3100	3200	140	55

Table 1: Sample of Raw Sensor Readings

We met some real-life challenges when we rolled out the system to the field. The gas sensors were easily affected by changes in humidity and temperature, which made their readings inaccurate. Also noise sensors had very high sensitivity and they would sometimes record loud noises at festivals or in construction sites which were completely unrelated to our monitoring areas. In some initial attempts, we also faced unstable Wi-Fi leading to short breaks in data transmission. These problems we handled in preprocessing step. We got rid of outliers, matched the missing values and also we evened up the signals. Ultimately, the data that was fed to our models was clean and trustworthy.

After data was cleaned, it was used for training and testing three different models: Decision Tree, Random Forest, and Multilayer Perceptron (MLP). A simple web dashboard was also drafted for the system. It gives the users an option to input sensor values manually or upload a CSV file and pollution prediction will be shown instantly. Fig 1, illustrate the dashboard that display air and noise pollution results side by side. For example, in one sample output, it predicted an AQI of 286. 93, which was classified as "Moderate, " along with a noise level of 76. 92 dB, classified as "High."

DOI: 10.48175/568

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Fig 1: Web Dashboard for Real-Time Air and Noise Pollution Prediction

To help users grasp our findings more quickly, we outfitted the dashboard with some visual aids that turned out to be quite effective. Rather than merely listing numbers, Fig 2 displays the raw sensor readings plotted over time, whereas the predicted AQI is represented by a dashed line. Besides that, the use of coloured background zones such as green, yellow, and red enables the users to do a quick check of the air quality levels being safe, moderate, or poor respectively

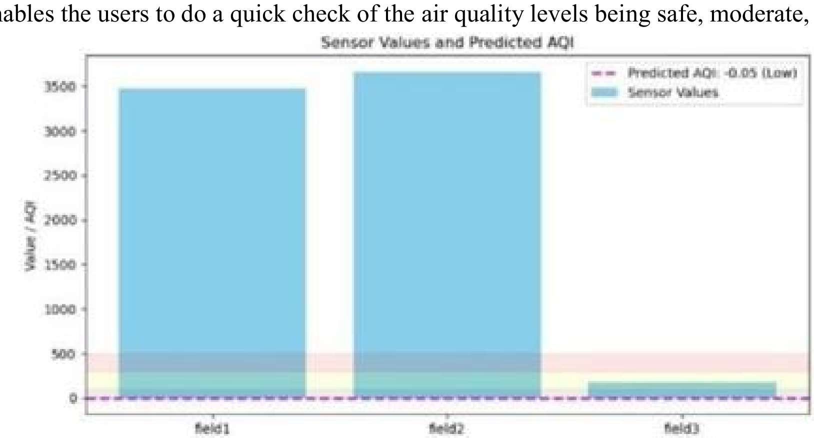

Fig 2.Sensor Readings and Predicted AQI Over Time

We also implemented a basic horizontal AQI indicator in Fig 3. Its colours correspond to a green, yellow and red scale, allowing you to immediately identify the predicted AQI level, visually. This feature is so user-friendly that anyone, even a non-technical person, can effortlessly grasp the present air quality situation.

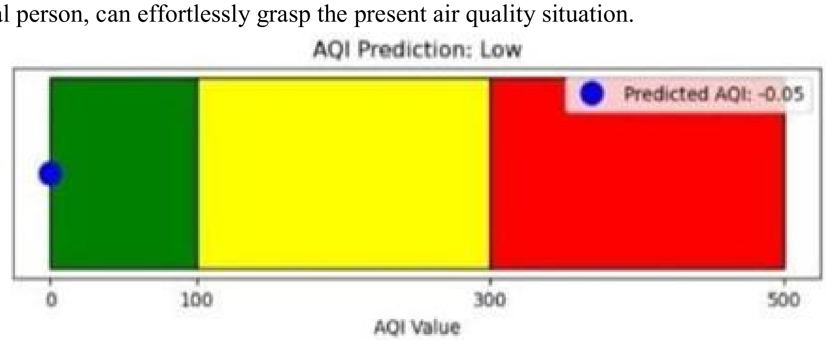

Fig 3. Horizontal Color-Coded AQI Prediction Indicator

Fig 4 is a time series graph connecting two sets of data, AQI and noise levels, by displaying them together in the line graph over time. Such a dual visualization particularly was a very insightful hardly that it revealed that air quality and

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noise levels often were in peak at the same time during traffic-heavy hours, pointing to the importance of monitoring both parameters at the same time rather than separately

Fig 4. Time-Series Visualization of Predicted AQI and Noise Levels

When volunteers took part in the study, a few of them mentioned that not only is the dashboard convenient, but they also like how it is color-coded, which makes it easier to read. Moreover, a few people mentioned that they changed their behaviour of going outside after the system showed high pollution levels, which means that the implementation has a very tangible effect on people's lives beyond just gathering data. Besides, school personnel utilized the historical data and export functionalities for environmental safety audits as part of their regular activities, which they found very handy.

According to the statistical results shown in Table 2, the MLP neural network attained the highest figure, i. e. 95. 1% accuracy with the corresponding values of precision, recall, and F1-score being

0. 95 each. Random Forest Recorder was 93. 6% accurate, Decision Tree Model 90. 2%. MLP's proficiency in modeling complex nonlinear relations between sensor inputs provided it with an advantage in situations where pollution levels fluctuated abruptly or in unexpected ways.

Model	Accuracy (%)	Precision	Recall	F1-score
Decision Tree	90.2	0.88	0.90	0.89
Random Forest	93.6	0.92	0.94	0.93
MLP Neural Network	95.1	0.95	0.95	0.95

Table 2: Performance Comparison of the Machine Learning and Deep Learning Models

The whole body of the results basically corroborates the proposition that merging IoT-oriented sensing with a mixture of machine learning and deep learning models represents a system that is technically a good fit but also very much in line with the needs of average users. Including the capability to monitor the real-time aspect of both air and noise pollution, clearly visualize trends, and give immediate forecasts will all in all make this system a very viable and major solution for smart environmental management in urban communities.

V. CONCLUSION

The newly designed IoT-based hybrid machine learning and deep learning system for real-time air and noise pollution monitoring manifests a boost in accuracy, scalability, and application-oriented capabilities. Firstly, the device integrates a small microcontroller named ESP32 that acts as a brain of the system, interconnected with air quality and gas sensors such as MQ135, MQ7, and MQ2 plus a microphone associated with the MAX9814 module.

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All the main parameters are recorded uninterruptedly and sent in real-time to the ThingSpeak cloud for further analysis and visualization. Secondly, a hybrid scheme of prediction based on combination of models like Decision Tree, Random Forest, and Multilayer Perceptron (MLP) models, showed good results in the experiments.

In particular, the MLP network obtains the greatest results, namely 95. 1% accuracy, and all the three precision, recall, and F1-score resulting to be 0. 95. This outcome illustrates the potential of the proposed model to reflect features in multi-sensor IoT data. Besides performing multi -input operations and noise management features, the system also adapts to changing environmental conditions conferring it reliability in real-world functioning. On top of that, owing to its cloud-based design, it is conveniently scalable in both urban and semi-urban areas.

The interactive web dashboard offers beautiful real-time visualizations and instant predictions that make it so much easier for the residents, institutions, and policemen to handle complex environmental data. Making the dashboard a medium that both connects technical innovation with everyday usability and effectively informs community is one of the great merits of this work. All in all, this paper serves as one of the milestones that demonstrate the usefulness of IoT and AI technologies for environmental monitoring. Besides, the study helps to make cities greener and cleaner by enabling more informed decisions and paving the way for the evolution of smart, healthy cities.

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