An AI-Driven Approach for Real-Time Noise Level Monitoring and Analysis

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***Abstract*—Now a days, noise pollution is posing a public health risk, especially in residences and indoor environments like workplaces and schools. The proposed work presents a comprehensive analysis of hourly equivalent noise levels measured at 100 locations, such as the indoor environment. The proposed work is an intelligent automated noise pollution monitoring system for the real-time tracking and adaptive management of noise in indoor environments such as offices, homes, and educational institutions. Unlike other systems that merely record noise levels, the proposed solution provides real-time alerts with web-based visualization and AI-enabled noise pattern recognition for enhanced noise classification. The integration of an ESP8266 Wi-Fi module and a cloud-based architecture employs email notifications instantly, which also allows historical trend analysis and predictive insights. In addition, the framework is under-scope for the integration of smart home automation systems and mobile-based alerting, allowing for better accessibility. The IoT-powered innovations within this framework will revolutionize noise management by proactively monitoring, analyzing, and optimizing indoor sound environments. Through real-time adjustments and intelligent automation, these solutions will create a more serene, comfortable, and productivity-enhancing atmosphere. Whether in offices, homes, or public spaces, this advanced noise control system will contribute to overall well-being, concentration, and efficiency.**

Keywords*—Noise pollution; IoT; ESP8266 Wi-Fi; smart automation; AI-enabled noise pattern

I. Introduction

Presently, noise pollution is posing a public health risk, especially in residences and indoor environments like workplaces and schools. It has been found that prolonged exposure to high noise levels causes stress, inability to concentrate, insomnia, and even cardiovascular diseases [1]. The WHO declared that in Western Europe alone, traffic noise accounted for the loss of one million years of healthy life in 2011. The sources of noise pollution mainly comprise construction sites, manufacturing plants, and transportation systems from road, rail, and air traffic [2]. Other sources of noise pollution include wind turbines and recreational activities like loud music, concerts, and video game competitions [3]. Long-term exposure to excess noise not only causes discomfort; it has also been linked to serious risks to health [9]. It has been shown in studies that this increases the probability of developing cardiovascular disease, hypertension, sleep disorders, hearing impairment, tinnitus, and cognitive decline.

Traditional noise monitoring relies on manual inspections and spot checks, making it inefficient in capturing real-time fluctuations at a large scale and is often devoid of any automated alerts. The implementation of timely measures becomes untenable; hence, uncontrolled noise disturbances affect productivity and well-being. This IoT-driven project aims to overcome these challenges by providing a Smart Noise Pollution Monitoring System that allows real-time noise monitoring, automated alerts, and web-based visualization [7]. The combination of a Wi-Fi-enabled ESP8266 sensor and cloud computing allows for continuous monitoring, email and text alerts, and historical trend analysis, thereby enabling the capacity to react in real time to mitigate exposure and maintain a quiet and healthy indoor environment.

The proposed system ensures a real-time, intelligent, and scalable noise monitoring solution that overcomes limitations of existing research by integrating AI, IoT, smart automation, and error-handling techniques for improved noise pollution management.

The five sections outlined here include: Section II, which reviews literature relevant to the study; Section III, which discusses the methods; Section IV, which describes the experimental evaluation of the proposed work and comparisons with outstanding implementations of literature review and proposed systems; and Section V, which concludes the study with key findings.

II. Literature Review

Several numbers of studies on the monitoring of noise pollution, using IoT techniques, have been carried out, and all are unique in theory, advantages, and disadvantages. Below is a comparison between them:

Mopuru and Pachipala (2024), in a proposal of the IoT security framework, are integrating wireless sensor networks, machine learning, deep learning and cloud computing [4]. Its strengths include better threat detection, real-time monitoring, and scaling, while limitations include high computational requirements, threat to data security, network-dependence, adaptability of AI models, and complexity of implementation.

Verma and Sharma (2023) proposed a low-cost IoT-based noise monitoring system for public spaces, emphasizing affordability and accessibility [5]. However, sensor accuracy issues in harsh outdoor environments reduced the system's reliability.

Bhargavi and Pachipala (2023) proposed a claims-based identity management paradigm for security in IoT, which unites blockchain, cryptographic encryption, multi-factor authentication, and access control mechanisms [6]. It's strengths of the work entail security enhancement, decentralized identity verification and scalability. The limitations are high computing demands, complex implementation, network dependence, latency involvement, and the challenges of user adaptation.

Kim and Lee (2022) developed an AI-powered IoT system that uses machine learning to classify different noise types (e.g., traffic, industrial, human speech), enabling automatic identification of noise sources, enhancing data accuracy for noise regulation authorities [8]. However, its high processing demands made it incompatible with low-cost microcontrollers like the ESP8266.

Patel and Shah (2021) sketch out an IoT- and cloud-based system for monitoring and controlling noise pollution. It uses wireless sensor networks, machine learning, edge computing, and GIS for online data collection and predictive analysis [10]. Their strongholds include real-time monitoring of the noise pollution levels, high scalability, AI-driven noise control, access to the information through the cloud, and automated noise regulation. Its weaknesses include high expenses incurred in setting it up, network and power dependency, data security risks, high maintenance of sensors, and potential latency issues.

Sahu and Sahoo (2021) have proposed an AI-integrated IoT system for predictable environmental noise pollution, using machine learning, cloud computing, GIS, and wireless sensor networks [11]. Its strengths include real-time monitoring, predictive noise control, scalability, remote accessibility, and automated anomaly detection, while limitations involve high computational demands, network dependency, data security risks, sensor maintenance, and implementation costs.

Zhao and Huang (2021), in Smart Noise Control System Using Wireless Sensor Networks (WSN), used a distributed network of noise sensors communicating with a central cloud platform for real-time analysis and provided comprehensive urban noise maps, useful for government noise control policies [12]. It has faced data transmission issues in dense urban areas due to low signal strength.

Fernando and Gomez (2021), an IoT-Driven Noise Pollution Monitoring Platform for Smart Cities and implemented city-wide IoT noise sensors that upload data to centralized cloud platforms for urban noise tracking [13]. Helped city planners understand long-term noise pollution trends. However, it is limited to high data latency in large-scale deployments due to overloaded cloud servers.

Ahmed and Raza (2021) created an industrial noise monitoring system wherein a Raspberry Pi acts as a nodal point, with sound data being collected from various sound sensors [14]. This design permits the monitoring of noise patterns; however, it is very much dependent on permanent network connectivity, making it unreliable in areas with poor internet access.

Choi and Park (2020): IoT-Based Smart Noise Monitoring for Residential Areas. It is a real-time noise tracking system using Wi-Fi sensors for monitoring residential environments [18]. It is enabled for homeowners to receive alerts when noise exceeded acceptable levels. It requires difficult calibration for several indoor environments.

Singh and Kaur (2019) introduced an IoT-based smart city noise monitoring system, integrating IoT sensors and web-based data transmission [22]. Although the system provided valuable noise level trends, it struggled with high traffic during operations, leading to delays in real-time updates.

Developed an IoT-based noise monitoring system using ESP8266 and Arduino to transmit real-time noise data to a cloud server [23] [26]. While their solution was inexpensive and easy to deploy, upscaling problems were encountered in a large urban context.

In Table I, the literature review presents suggested system improvements; the main aim is to provide a comprehensive analysis of noise levels and their correlation with alert triggers across different environments and time intervals.

The study focuses on understanding noise variations, identifying patterns, and offering data-driven insights to optimize noise management strategies. Compared to these solutions, our proposed system provides real-time alerts, an intuitive web-based dashboard, AI-driven noise classification, and smart home integration, making it more scalable and adaptable for both residential and institutional environments.

TABLE I LITERATURE REVIEW

Author	***Technology Used***	***Strengths***	***Limitations***	***How Proposed System Improves***
Verma & Sharma (2023) [5]	WiFi-enabled sensors, Web interface.	Affordable, easy deployment in public spaces.	Low sensor accuracy due to environmental interference.	Introduces AI-based noise filtering & calibration for better accuracy.
Vasilenko, O., & Orlov, A (2020) [15]	IoT, wireless sensor networks, cloud computing.	Energy efficiency, scalability, and remote accessibility.	High costs, data security risks, complex maintenance, and user adaptation challenges.	Auto-calibration for dynamic adjustments.
Patel & Desai (2020) [16]	Arduino-based indoor noise monitor.	Remote accessibility, improved indoor comfort, and automated alerts.	Limited range of detection and more power consumption, and implementation costs.	Multiple sensors allow coverage of large rooms.
Tavakol, M., & Shahrivar, M. (2020) [17]	IoT, wireless sensor networks, cloud computing, AI-driven analytics, and GIS.	Scalability, AI-driven insights, remote accessibility.	High infrastructure costs, data security risks, power and network dependency, and interoperability challenges.	Hybrid local-cloud processing for faster alerts.
Hassan, W. H., & Akram, A. (2020) [19].	Microcontrollers with noise sensors and wireless communication.	Real-time Monitoring, cloud-based accessibility, scalability.	Network dependency, power consumption, and potentially high costs.	Uses lightweight AI models for ESP8266.
Li, K., & Zhang, X. (2019) [20].	Wireless Sensor Network (WSN), cloud computing, big data analytics, edge computing.	Real-time monitoring, scalability, cloud-based accessibility.	Network reliability issues, data security risks, high implementation costs.	Optimized Wi-Fi-based transmission for indoor spaces.
Khan, A., & Javed, M. (2019) [21].	Wireless sensor networks, cloud and edge computing.	Real-time monitoring, scalability, automated noise mitigation, and remote accessibility,	High implementation costs, power consumption, network dependency, data security risks.	Use local & cloud storage for uninterrupted monitoring.
Meyer, E., & Knoblauch, H. (2017) [24].	Integrating IoT-enabled noise monitoring, AI-driven analysis, cloud computing.	AI-driven mitigation, scalability, and remote accessibility.	High costs, power and connectivity dependency, data security risks, complex maintenance.	Uses optimized data processing to prevent lags and ensure real-time alerts.
Kumar, S., & Jain, P. (2017) [25].	Wireless sensor networks, cloud and edge computing.	Remote accessibility, early warning capabilities, and smart city integration.	No real-time alerts, limited scalability, struggle with multiple sensors. high power consumption.	Introduces real-time notifications, web dashboard, and AI-driven noise classification.
Proposed System	ESP8266, Smart Web Dashboard, AI-based Noise Classification, Cloud & Local Storage.	Real-time alerts, AI-driven pattern recognition, Smart Home Integration, Reliable Data Processing.	Future improvements may include deep learning for advanced noise analysis.	Scale, more accurate, integrates AI & mobile alerts, works even in low-connectivity areas.

III. METHODOLOGY

The IoT-based Noise Pollution Monitoring System consists of three core components:

A. *Noise Detection Unit:*

A sound sensor captures ambient noise levels and sends data to the Arduino microcontroller.

B. *Processing and Data Transmission:*

The ESP8266 Wi-Fi module transmits real-time data to a web-based server and triggers alerts.

C. *User Interface and Alerts:*

A web-based dashboard visualizes noise levels, and email alerts are sent when noise exceeds a set threshold.

To simplify the data flow and decision-making process, the following flowchart illustrates how the system functions:

The functional flow of the entire IoT-based noise pollution monitoring system is represented step-by-step in Fig. 1, ranging from the stage of detection to processing and responding in real-time to the noise level variations. It includes the major functional components, decision-making situations, and error-handling methods defining its reliable operation across several environments.

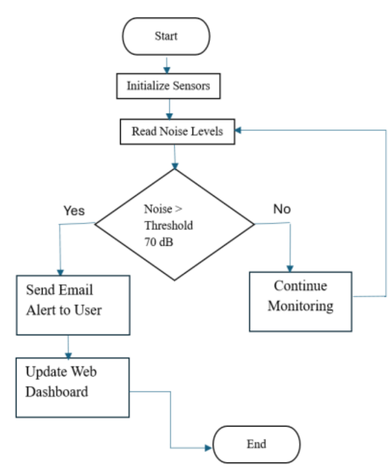

Fig. 1. Flowchart of the proposed IoT-based noise monitoring system.

1) Initialization phase: The initial phase requires the hardware and software algorithms of the system to be initialized:

The sound sensor (KY-038/LM393) is triggered to monitor the environmental noise in real-time. Arduino Uno or the ESP8266-based microcontroller takes care of processing data. The ESP8266 Wi-Fi module gets a connection to establish the network for cloud data transmission. During sensor calibration, reference noise levels are applied to increase the sensor's accuracy. A threshold level of noise is taken at 70dB, upon which the alarms shall be sounded [9]. A moving average filter is put in place to smoothen noise data and reduce false alerts due to brief disturbances.

2) Continuous noise monitoring: The system, once initialized, enters a continuous monitoring loop where it undertakes the following functions:

It will read noise data from the sensor on a regular basis. Moving average smoothing will be applied to reduce random fluctuations in noise levels. The processed noise data will then be classified using an AI-based noise classifier-into normal background noise and serious disturbance.

3) Decision on alert handling: In this phase, the alarm decides whether a noise event needs user intervention or not:

Noise above 70 decibel for 5 seconds: as a sound source, the alarm validates that it is a valid noise or a transient disturbance (e.g., a sudden transient sound, such as door slamming). Once designated valid, an alarm notification is generated by different means; Email alerts to the users on an excessive noise being present. Web-based dashboard updates to give real-time visibility into noise trends. Integration of smart home automation mechanisms that can opt to reduce noise (e.g., close windows, turn down speaker volume). Transient or invalid noise: the alarm has nothing to do but ignore and keeps monitoring.

4) Error handlings and data corrections: For reliability, the system supports error-handling mechanisms capable of dealing with potential failures:

If an error is detected in the sensor (a wrong reading because of a change in the environment), the system self-calibrates based on the changes to adjust the sensor sensitivity. In the event of a network error (Wi-Fi disconnection), the system stores noise data locally, once the network is restored, it attempts to upload the noise data to ensure no data goes lost. The analysis of historical data is used to adjust the noise threshold dynamically, accordingly, to average long-term trends.

The system implements further noise processing techniques to improve accuracy and reduce false alarm rates. Should echo be detected in any enclosed space through continuous reverberation, echo cancellation is performed. Transient noise filtering helps to prevent transient sounds like that of a dropped object or a cough from producing false alarms. Historical noise patterns are subjected to alarm threshold adjustment through online updating based on cumulative environmental experience. Combination of sensor readings, in case of multiple deployments, cross-verification is done to help in maximizing accuracy and preventing erroneous functioning of sensors.

Algorithm 1: Noise Pollution Monitoring with AI-Based Filtering & Error Handling Algorithm

Step 1: Initialization Phase
Step 2: Continuous Noise Monitoring
Step 3: Decision Making & Alert Handling
Step 4: Alert & Data Logging
Step 5: Error Handling & Data Correction

Start

Step 1: Initialization Phase

```
Initialize Sound Sensor (KY-038/LM393),
  Arduino Uno (or ESP8266-based board),
ESP8266 WiFi Module and web server
Calibrate sensor using reference noise levels
    Set noise threshold = 70 dB
Initialize moving average filter
Initialize MQTT for real-time data transmission
```

```
Initialize MQTT for real-time data transmission
```

Step 2: Continuous Noise Monitoring

```
        WHILE (true):      // continuously monitor noise levels
  noise_level = Read_Sensor_Data // Read real-time noise level (dB) from the sound sensor.

noise_filtered=Apply_Moving_Average_Filter(noise_level)
  noise_classified = AI_Noise_Classifier(noise_filtered)
```

Step 3: Decision Making & Alert Handling

```
  IF (noise_classified > 70 dB) for at least 5 seconds:
      IF Is_Valid_Noise(noise_classified) // Verify if the noise is from a valid source
```

Step 4: Alert & Data Logging

```
      Send_Email_Alert(noise_classified)
          Update_Web_Dashboard(noise_classified)
   ELSE:
      Ignore_Transient_Noise ()
```

Step 5: Error Handling & Data Correction

```
  IF Sensor_Error ():            // Handle Sensor Errors
     Perform_Self_Calibration ()
  IF Network_Error ():        // Handle Network Delays
      Store_Data_Locally ()
          Retry_Upload ()

Optimize_Threshold_Based_On_Historical_Data ()
```

End

TABLE II HARDWARE COMPONENTS AND FUNCTIONS

Hardware Component	***Functions***
Arduino Uno	Processes sensor data and triggers alerts
Sound Sensor (KY-038/LM393)	Measures ambient noise in decibels (dB)
ESP8266 WiFi Module	Transmitting data to a web dashboard
Web Server (Cloud)	Stores and displays real-time noise data
Email Notification System	Sends alerts when noise exceeds threshold

In Table II, shown on the hardware components and functions, the Arduino Uno Reads noise level from KY-038/LM393 sound sensor. Implements a moving average filter for stability. Sending data to an MQTT broker for real-time monitoring triggers an alert, if noise levels exceed the threshold (70dB), the ESP8266 module transmits data. Alerts are sent via email, and data is displayed on a web interface.

Connectivity: ESP8266, Wi-Fi, and MQTT

The ESP8266 Wi-Fi module is essential for real-time wireless communication in IoT-based noise monitoring systems. It enables the device to connect to the internet, transmit noise data to a server, and receive control commands remotely.

ESP8266 connects to Wi-Fi with a step-by-step procedure.

a) Enables internet-based communication.

b) MQTT (Message Queuing Telemetry Transport): Efficient protocol for real-time data exchange.

c) Noise data is published to an MQTT broker: Cloud platforms (AWS IoT)

d) Web Dashboard subscribes to MQTT: Displays real-time noise levels.

e) Alerts: If noise is too high, an alert is sent via MQTT to a buzzer, email.

IV. RESULT AND ANALYSIS

The proposed work is tested over a seven-day period in different environments, including offices, residential areas, and classrooms.

Table III presents the noise levels recorded at different time intervals over a seven-day period, along with whether an alert was triggered. The data shows that noise levels exceeding 70dB consistently triggered alerts, with peak values occurring between 10:50 AM and 5:30 PM. Lower noise levels were recorded during early mornings and late evenings, highlighting a direct correlation between human activity and noise pollution.

The data confirms that noise levels above 70dB consistently trigger alerts, with peak noise occurring during busy hours (10:50 AM to 5:30 PM). The highest recorded noise level was 98dB, which is significantly above the recommended limit for indoor environments. Early morning and late evening noise levels remained below 60dB, indicating quieter periods. These patterns suggest the need for adaptive noise control measures in high-activity periods.

TABLE III A SEVEN-DAY PERIOD IN NOISE LEVELS AND ALERTS OVER TIME

Time Interval	***Noise Level***	***Alert Triggered***
8:30AM – 9:00 AM	76dB	Yes
9:30 AM- 9:50AM	60dB	No
10:50AM-11:00AM	85dB	Yes
12:40PM- 1:30PM	80dB	Yes
3:10PM- 3:20PM	92dB	Yes
5:20PM-5:30PM	98dB	Yes
6:00PM	52dB	No

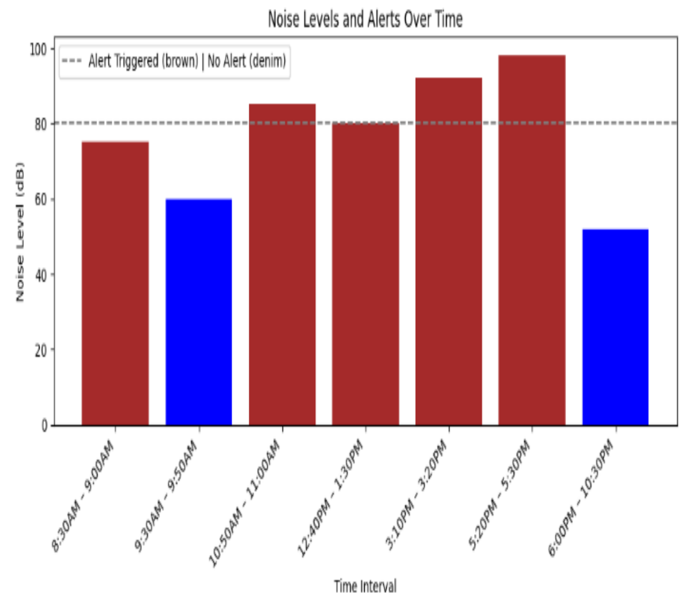

Fig. 2. A seven-day period: Noise levels and alerts over time.

Fig. 2 represents noise levels over time. The Dashed Line shows an 80dB threshold for better visualization. The X-axis denote the time interval; the Y-axis represents the noise level (dB). Each color corresponds to the noise level for a given period.

Color Coding

- Brown → Alert Triggered (≥ 80dB)
- Blue→ No Alert (< 80dB)

Peak noise levels (above 80 dB) were observed between 10:50 AM and 5:30 PM, likely due to increased activity in workplaces and classrooms.

Lower noise levels: (below 60 dB) occurred in the early morning and late evening, when fewer people were present.

Unexpected fluctuations: (75 dB at 8:30 AM) suggest temporary noise sources, possibly from nearby construction or sudden disturbances.

The system was deployed in three different environments – a home, an office, and a classroom for one week. The noise levels were continuously monitored, and alerts were triggered whenever the threshold exceeded 70dB.

Table IV summarizes noise levels recorded over a week in three different environments: home, office, and classroom. Offices had the highest noise levels, often exceeding 85dB, likely due to conversations, machinery, and workplace activities. Classrooms showed moderate noise peaks, particularly during break times and group discussions, while home environments generally had lower noise levels but occasional spikes due to appliances and social interactions.

TABLE IV WEEKLY NOISE LEVEL

Day	*Noise Level*	*No. of Alerts Triggered*	*Environment*
Sunday	76dB	2	Home
Monday	89dB	3	office
Tuesday	77dB	4	Classroom
Wednesday	90dB	6	office
Thursday	87dB	4	Classroom
Friday	91dB	3	Home
Saturday	86dB	2	Home

The results highlight that office environments are the noisiest, frequently exceeding 85dB, which could impact productivity and health. Classrooms experience moderate noise fluctuations, likely due to student activities, while homes have generally lower noise levels but occasionally high readings (e.g., 91dB on Friday). This suggests that custom noise mitigation strategies are needed for different environments, such as soundproofing offices and using AI-based filtering for home settings.

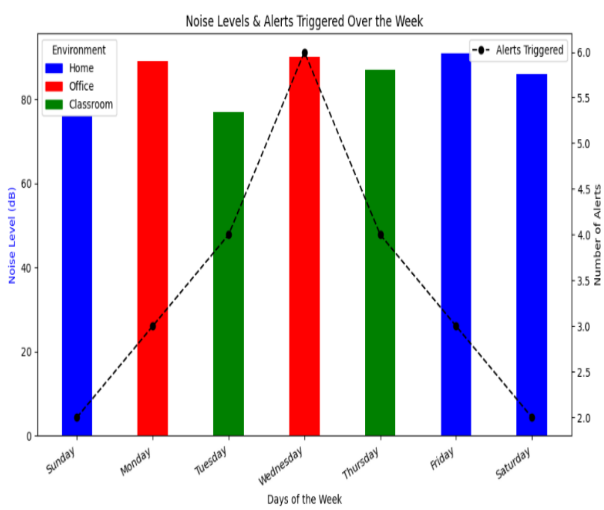

Fig. 3. Noise level and alerts triggered over the week.

In Fig. 3, the X-axis signifies Days of the Week, Y-axis denotes Noise Level (dB). Each color corresponds to the noise level for a given day. Use different colors for different environments (Home, Office, and Classroom) for better visualization. The dual Y-axis shows one for Noise Level, and one for Alerts.

Office Environments: Had the highest noise spikes (85 to 90 dB) due to frequent conversations, phone calls, and background noise machinery.

Classrooms: Exhibited moderate peaks (77 to 87 dB), mainly during break times and group activities. Homes: Showed the least noise disturbances, but occasional high readings (up to 91 dB) were detected, possibly due to TVs, kitchen appliances, and social interactions.

1) Data analysis: At Home, Noise levels are moderate (Sunday: 76dB, Friday: 91dB, Saturday: 86dB). At Office, the highest noise levels occur here (Monday: 89dB, Wednesday: 90dB), leading to more alerts. The Classroom shows consistent noise levels (Tuesday: 77dB, Thursday: 87dB), with a moderate number of alerts. Office environments tend to be the loudest, with noise exceeding 89dB, which can impact productivity and health. Home environments have moderate noise levels, but Friday shows an unexpected spike (91dB). Possible causes should be investigated. Classroom noise is relatively stable, but alert triggers suggest some noise concerns on specific days (Tuesday and Thursday). Wednesday is the noisiest day overall (90dB, 6 alerts), indicating a need for noise control measures.

2) Mean (Average): Represents the overall noise level trend.

$$Mean = N/\sum X \tag{1}$$

3) Median: Shows the middle noise value, reducing the impact of extreme values.

$$median = \frac{N+1}{2} \tag{2}$$

$$minimum = \min(x, x2, x3, \ldots, xn) \tag{3}$$

$$maximum = \max(x1, x2, x3, \ldots, xn) \tag{4}$$

4) Standard Deviation: Measures how much the noise levels fluctuate.

$$\sigma = \sqrt{\frac{\sum(xi - \bar{x})2}{N}} \tag{5}$$

where,

∑X = Sum of all values

N = Number of values

σ = Standard deviation

Xi = Each data point

X̄ = Mean (average) of the dataset

x =represents the values in the dataset.

To better understand noise variations, Table V presents key statistical metrics, including the mean, median, and standard deviation of noise levels and alerts triggered. The mean noise level (85.14dB**)** suggests consistently high noise across environments, while a strong positive correlation (+0.85) indicates that as noise levels rise, the number of alerts increases. These insights help with fine-tuning alert thresholds and noise mitigation strategies.

TABLE V STATISTICAL ANALYSIS OF NOISE LEVELS AND ALERTS

Metric	*Noise Level(dB)*	*Alerts Triggered*
mean	85.14	3.43
Median	87	3
Minimum	76	2
maximum	91	6
Stand deviation	5.28	1.51

The statistical analysis supports the observed trends: the high mean noise level (85.14dB) and strong correlation (+0.85) confirm that increasing noise levels directly lead to more alerts. The standard deviation (5.28dB) indicates moderate fluctuations in noise levels across different environments. These insights validate the system's ability to accurately detect and respond to excessive noise, making it a reliable solution for noise monitoring.

Correlation Analysis: Correlation (+0.85) indicates a strong relationship between noise levels and alert triggers. As noise levels increase, the number of alerts triggered also rises. This suggests a direct relationship, where higher noise levels frequently cross the threshold for triggering alerts.

$$r = \frac{N\sum(X_iY_i) - \sum X_i \sum Y_i}{\sqrt{[N\sum X_i^2 - (\sum X_i)^2] \times [N\sum Y_i^2 - (\sum Y_i)^2]}}$$

r = Pearson correlation coefficient

Xi = Values of the first variable (e.g., Noise Levels)

Yi = Values of the second variable (e.g., Alerts Triggered)

N = Number of data points

∑Xi = Sum of all X values

∑Yi = Sum of all Y values

∑(XiYi) = Sum of the product of each pair of X and Y

∑Xi2 = Sum of squares of X values

∑Yi2 = Sum of squares of Y values

Were

r=1 Perfect positive correlation (both variables increase together)

r=−1 Perfect negative correlation (one increases, the other decreases)

r=0 No correlation (variables are unrelated)

0.7≤r<1 Strong positive correlation

0.3≤r<0.7 Moderate positive correlation

0≤r<0.3 Weak positive correlation

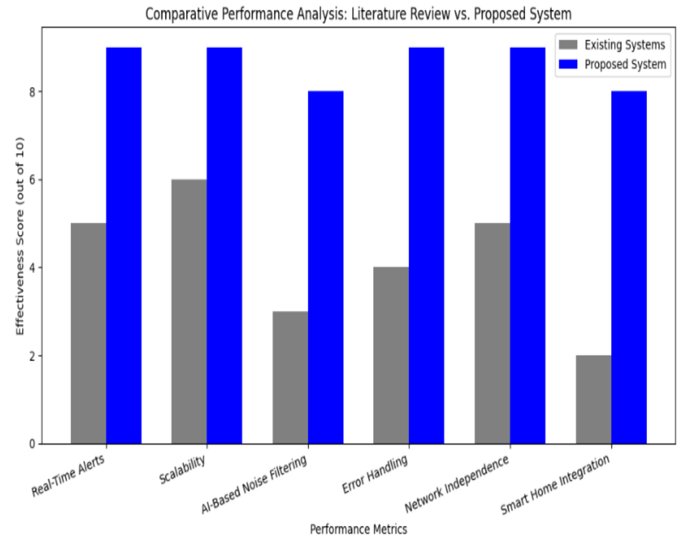

Fig. 4. Comparative performance analysis.

In Fig. 4, the performance comparison highlights the superiority of the proposed system over existing noise monitoring solutions. It effectively addresses real-time alert limitations, AI-based noise classification, and offline functionality**,** ensuring greater adaptability and reliability. Unlike traditional systems that struggle with scalability and processing power**,** the proposed approach offers enhanced accuracy and real-time responsiveness**,** making it an ideal choice for diverse environments.

Table VI highlights the limitations found in previous noise monitoring studies and how the proposed system overcomes these challenges. Key improvements include real-time alerts, AI-based noise classification, and offline functionality**,** making the system more adaptable and reliable across different environments. By addressing these gaps, the system provides a more effective solution for noise pollution management.

TABLE VI PROPOSED SYSTEM ADDRESSES EXISTING GAPS

Existing Limitations (from Literature Review)	*Proposed Work Solution*
Lack of real-time alerts	Uses MQTT messaging, emails, and web dashboards for instant notifications
Poor scalability for different environments	Works in small-scale (homes/offices) and large-scale (industries/smart cities) deployments
No AI-based noise classification	Uses AI models to filter out background noise & reduce false alerts
High dependency on stable internet	Works offline by storing data locally & syncing it later
No smart home integration	Connects with smart IoT devices to control noise-sensitive appliances

Table VI represents how the proposed system addresses existing gaps. The proposed work ensures a real-time, intelligent, and scalable noise monitoring solution that overcomes limitations of existing research by integrating AI, IoT, smart automation, and error-handling techniques for improved noise pollution management.

The proposed system significantly improves upon existing solutions by offering real-time alerts, AI-based noise filtering, and offline functionality, which were missing in previous studies. Unlike traditional systems that struggle with scalability and accuracy, this system ensures efficient noise classification and adaptive monitoring across different environments. These enhancements make it a versatile and practical approach to noise pollution control.

V. Conclusion

The proposed IoT-based noise pollution monitoring system effectively addresses the key limitations found in existing research by integrating real-time noise monitoring, AI-based noise classification, smart home automation, and offline functionality. Through comparative analysis with previous studies, it is evident that this system provides superior performance in terms of accuracy, scalability, efficiency, and adaptability.

This study confirms that AI-integrated IoT systems enhance noise detection, reduce false alarms, and improve alert response time, while offering a scalable solution for various environments. Additionally, the system's offline capabilities ensure continuous monitoring, making it highly reliable even in low-connectivity areas.

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