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IMPLEMENTATION OF NOISE MAPPING AND PREDICTION SYSTEM USING IOT AND DEEP LEARNING FOR URBAN NOISE POLLUTION

Labdhi Doshi
Dept. of Internet of Things
Thakur College of Engineering and Technology
Mumbai, Maharashtra, India

Soham Kadam
Dept. of Internet of Things
Thakur College of Engineering and Technology
Mumbai, Maharashtra, India

Tanmay Patade Patil
Dept. of Internet of Things
Thakur College of Engineering and Technology
Mumbai, Maharashtra India

Abstract— **Urban noise pollution is an escalating concern in modern cities due to rapid urbanization, industrialization, and rising traffic volumes. Prolonged exposure to excessive noise has detrimental effects on human health, including sleep disturbances, cardiovascular issues, and psychological stress. Existing noise monitoring solutions are often expensive, static, and lack predictive capabilities.**

This paper presents the implementation of an Internet of Things (IoT) based Noise Mapping and Prediction System that leverages low-cost ESP32 microcontrollers, digital microphones, and cloud platforms for real-time monitoring. The collected data is processed and visualized as noise maps using Geographic Information Systems (GIS). Furthermore, a deep learning framework, specifically Long Short-Term Memory (LSTM), is proposed for predicting future noise levels. This system enables real-time monitoring, predictive analysis, and interactive visualization, providing an efficient solution for smart cities to mitigate noise pollution.

Keywords— **Noise Mapping, IoT, ESP32, Deep Learning, Urban Noise, Smart Cities**

I. INTRODUCTION

Urban noise pollution has become a critical environmental and public health issue in rapidly urbanizing cities. Continuous exposure to elevated noise levels is linked with adverse effects such as sleep disturbances, hearing loss, cardiovascular problems, and increased stress [1], [2]. The major contributors to urban noise include road traffic, industrial activities, construction work, and crowd gatherings, all of which significantly deteriorate the quality of life in densely populated areas [3].

Existing noise monitoring systems, though effective, are often expensive, static, and lack the ability to provide real-time data or predictive insights [4]. Moreover, these systems are difficult to scale in developing regions where cost and accessibility are major concerns [5]. Recent advancements in the Internet of Things (IoT) and machine learning technologies have opened new possibilities for smart and affordable environmental monitoring [6]. IoT-enabled low-cost sensors can continuously capture environmental data, while deep learning models can predict noise patterns and future noise levels with high accuracy [2], [4].

This research aims to implement a real-time Noise Mapping and Prediction System that integrates IoT devices with deep learning algorithms. By leveraging ESP32 microcontrollers, I²S microphones, and cloud storage, the system captures and maps noise data from different urban locations. In the next phase, predictive models such as Long Short-Term Memory (LSTM) networks will be employed to forecast noise levels, providing valuable insights for city planners, environmental agencies, and the public. The system is designed to be scalable, cost-effective, and energy-efficient, making it suitable for smart city applications worldwide.

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II. LITERATURE REVIEW

Several studies have investigated noise monitoring, mapping, and prediction systems to address the challenges of urban noise pollution.

Liu et al. [1] introduced intelligent noise mapping frameworks that integrate artificial intelligence (AI) and edge computing, emphasizing the need for predictive models in real-time urban monitoring.

Albahri et al. [2] conducted a comprehensive review of IoT-enabled noise mapping systems, focusing on sensor technologies, system architectures, and communication protocols, while highlighting their potential in smart city environments.

Alsboui et al. [3] demonstrated GIS-based noise mapping enhanced with machine learning, enabling multi-modal environmental monitoring and improved spatial noise prediction.

Turchet et al. [4] proposed the concept of the Internet of Sounds, leveraging sound event detection and edge AI techniques to enhance the responsiveness of noise-aware smart city applications.

Bhattacharjee and Roy [5] utilized noise pollution data for traffic flow prediction, showcasing the potential of sound-based datasets in urban planning and mobility management.

Musleh et al. [6] explored collaborative IoT frameworks for industrial noise mapping, emphasizing the importance of scalable and energy-efficient architectures for large-scale deployment.

Together, these studies establish the foundation for integrating IoT with deep learning techniques to develop practical, scalable, and predictive noise monitoring systems for urban environments.

III. SYSTEM DESIGN AND ARCHITECTURE

The proposed system for urban noise monitoring and prediction is organized into three primary layers:

A. IoT Hardware Layer-

This layer is responsible for data acquisition and on-site processing. The ESP32 microcontroller serves as the central control unit due to its low power consumption, Wi-Fi capability, and edge computing support. The INMP441 digital microphone is integrated for capturing environmental noise levels with high sensitivity and low self-noise. To enable spatial awareness, a GPS module provides real-time geotagging of noise data, allowing accurate mapping of noise distribution across urban locations. An OLED display is incorporated to present on-site readings and device status for quick user validation.

B. Cloud and Data Layer-

Once acquired, the noise and location data are transmitted to cloud platforms such as ThingSpeak or Firebase, which support real-time data streaming, secure storage, and easy retrieval. These platforms provide APIs and dashboards that facilitate preliminary visualization and analysis. The cloud also enables scalability, allowing integration of multiple IoT nodes for city-wide deployments.

C. Analytics and Visualization Layer-

In this layer, the stored data undergoes advanced processing. Interactive noise mapping is achieved using a Python-based dashboard built with Streamlit and Folium, which internally leverages the Leaflet.js mapping library to overlay geotagged acoustic data on dynamic maps. This provides real-time visualization of high-noise zones and temporal variations without requiring heavyweight GIS software such as QGIS or ArcGIS. Additionally, Matplotlib and Seaborn are employed to generate statistical and time-series plots for deeper analysis. For predictive modeling, a Long Short-Term Memory (LSTM) deep learning framework is proposed to forecast future noise pollution trends based on historical data, enabling proactive decision-making for urban planning and policy-making.

- **System Workflow**

The overall workflow begins with noise data acquisition through IoT devices, followed by wireless transmission to the cloud. The cloud stores and organizes the data, which is then processed to generate noise maps. Finally, the predictive deep learning module analyzes historical and real-time datasets to forecast future noise levels.

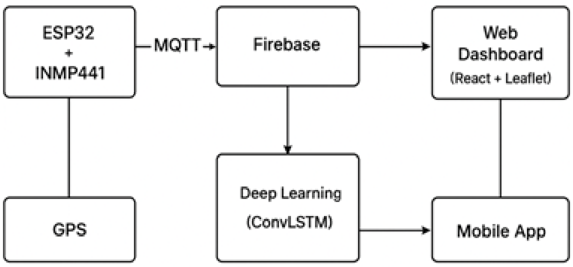


Fig. 1. Block Diagram of System Architecture

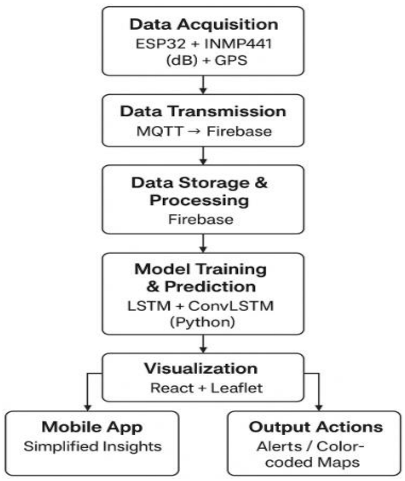


Fig. 2. Flowchart of System Workflow

This modular architecture ensures flexibility, scalability, and adaptability for future enhancements, such as integration with other environmental parameters (e.g., air quality or traffic density).

IV. IMPLEMENTATION

A. Hardware Implementation-

The hardware prototype is built on the ESP32 DevKit V1 microcontroller, chosen for its low power consumption, dual-core processor, and integrated Wi-Fi support. The INMP441 MEMS digital microphone is interfaced through the I²S protocol to capture high-fidelity environmental noise levels. To enable geospatial tagging, the NEO-6M GPS module provides latitude and longitude coordinates, ensuring accurate spatial mapping. A 0.96-inch OLED display (I²C interface) is used for local monitoring, displaying real-time noise levels and system status. The system is powered by a regulated 5V supply, supporting continuous field operation.

Table -1 Hardware Components

Sr. No.	Component	Specification	Quantity
1	ESP32 Dev Board	Wi-Fi enabled microcontroller	1
2	INMP441 Microphone	I²S Digital MEMS Mic	1
3	GPS Module NEO-6M	Geolocation tracking	1
4	OLED Display	0.96” I²C display	1
5	Power Supply	5V regulated	1

B. Software Implementation-

The system software is developed using the Arduino IDE with firmware programmed in C/C++. The ESP32 collects acoustic data from the INMP441, processes it locally, and transmits the results via HTTP or MQTT protocols. Data is pushed to ThingSpeak, which act as real-time cloud databases. These platforms allow secure storage, streaming, and easy access to measurements for further analysis.

For visualization, a Python-based dashboard is implemented using Streamlit and Folium. The dashboard automatically fetches data from ThingSpeak, generates time-series plots of noise levels, and overlays GPS-tagged readings on an interactive geospatial heatmap. This approach eliminates the need for external GIS tools such as QGIS, making the visualization process lightweight and real-time.

The modular design ensures interoperability with advanced analytics frameworks, enabling future integration of machine learning models such as LSTM for predictive noise level forecasting.

Table -2 Software Technology Stack Utilized in the Implementation of the IoT and Deep Learning-based Noise Mapping and Prediction System

Category	Tools / Technologies Used	Purpose / Description
IoT Communication	MQTT Protocol	Transmits sensor data to cloud in real time
Cloud Platform	Firebase	Real-time database for data storage and retrieval
Data Visualization	ThingSpeak	Cloud dashboard for graphs and analytics
Backend	Python, Flask	Data handling, preprocessing, and ML model integration
Machine Learning / AI	TensorFlow, Scikit-learn, LSTM + ConvLSTM	Noise prediction and pattern analysis
Frontend	React.js, Leaflet.js, Google Maps API	Web dashboard for visualization and insights
Mobile Application	React Native / Flutter	User access to alerts and simplified insights

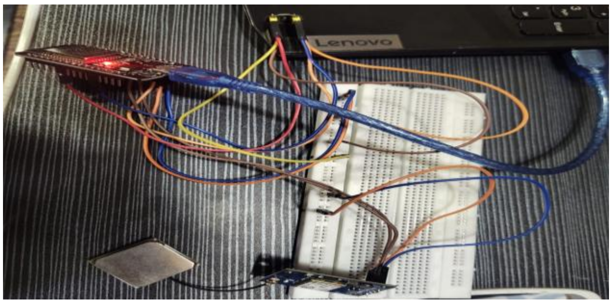


Fig. 3. Hardware Prototype Setup

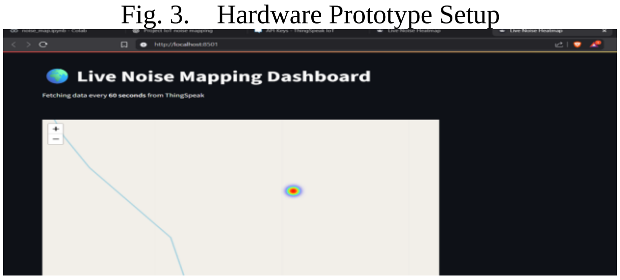


Fig. 4. Dashboard/ Noise Map Snap

This integrated implementation ensures seamless interaction between hardware and software components, enabling scalable deployment in urban environments.

V. PREDICTION MODULE (DEEP LEARNING)

To extend the system beyond monitoring and enable proactive urban noise management, a Long Short-Term Memory (LSTM) network is proposed for predictive analytics. The LSTM model is selected because of its proven capability to capture long-term temporal dependencies in sequential data, making it well-suited for time-series forecasting of noise levels.
The model will be trained using two data sources:

1. Collected sensor data from the IoT nodes deployed in urban areas.
2. Benchmark datasets such as UrbanSound8K, which contain diverse urban sound events (traffic, construction, crowd, etc.).

The training process involves preprocessing raw audio into numerical features such as decibel levels, Mel-Frequency Cepstral Coefficients (MFCCs), and spectrograms. These features are then fed into the LSTM layers for temporal pattern learning.
The LSTM network will output predicted short-term and long-term noise levels, enabling early detection of high-noise zones and supporting preventive actions by municipal authorities.

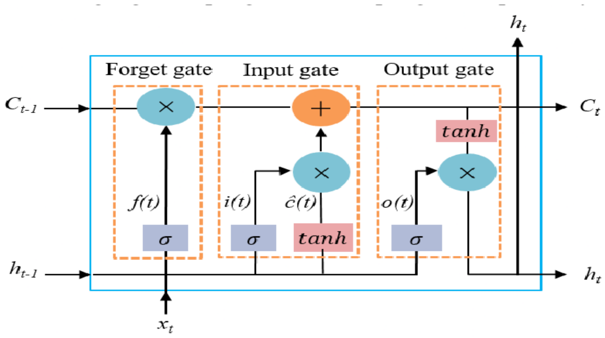


Fig. 5. Proposed LSTM Architecture Diagram – showing input features → LSTM layers → Dense layer → Predicted noise levels

VI. RESULT AND ANALYSIS

The prototype system was tested under controlled conditions to validate its core functionalities. The following preliminary results were obtained:

I. **Real-time noise acquisition**: The ESP32 DevKit V1 with INMP441 microphone successfully recorded ambient sound levels during test runs.

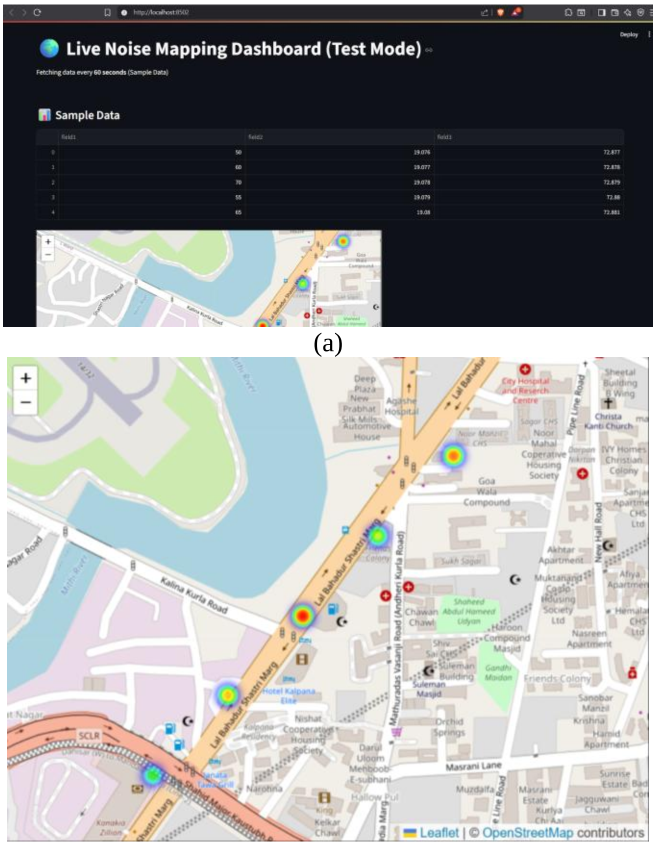
II. **Cloud integration**: Sensor readings were transmitted and stored in Firebase without data loss, confirming seamless communication between the IoT device and cloud layer.

III. **Noise mapping**: Sample datasets were visualized using Folium (Leaflet.js) within a Streamlit-based dashboard, producing interactive heatmaps that distinguish areas of relatively higher and lower noise intensity.

IV. **Geospatial tagging**: Test data with GPS coordinates confirmed the ability to link noise levels to specific locations for future large-scale mapping.

Table -3 Sample Dataset

field1(Noise level (dB))	field2(Latitude)	field3(Longitude)
50	19.076	72.877
60	19.077	72.878
70	19.078	72.879
55	19.079	72.880
65	19.080	72.881



(a)

(b)

Fig. 6. (a) Homepage of the Live Noise Mapping website showing sample data, (b) Interactive dashboard showing real-time noise visualization with Leaflet and OpenStreetMap integration.

The preliminary analysis suggests that the system is capable of identifying noise variations across different environments.

In extended field deployment, this will allow detection of traffic-dense and industrial zones exceeding the WHO recommended thresholds (>70 dB), thereby confirming its potential use in smart city noise management.

A prototype mobile application has been developed using Android Studio to visualize real-time noise data, historical trends, and predictive analytics for end-users. Although certain functionalities, such as personalized alerts and cloud-based synchronization, are under development, the app aims to empower users with insights into their personal noise exposure levels and nearby high-noise zones. The mobile interface provides an intuitive, location-aware noise dashboard that supports community participation in environmental awareness.

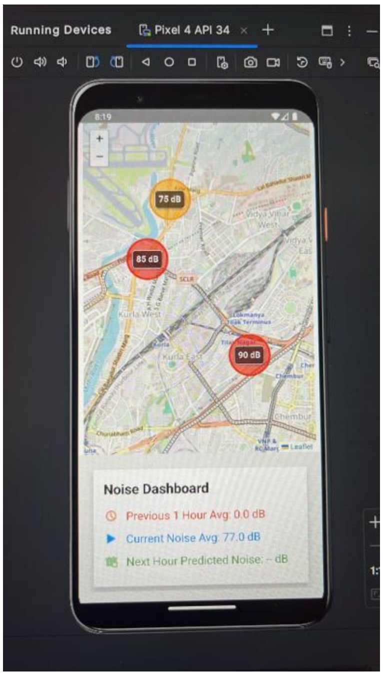


Fig. 7. Prototype mobile application interface showing real-time noise levels and location-based visualization on Google Maps.

VII. APPLICATIONS

The proposed Noise Mapping and Prediction System has diverse applications across multiple domains:

***A.* Smart Cities** –
In modern urban ecosystems, the integration of IoT-enabled sensors with noise mapping platforms can revolutionize environmental monitoring. The proposed system can serve as a core component of smart city architecture, facilitating continuous, real-time noise data acquisition and intelligent analysis. This data supports evidence-based governance by helping authorities identify problem areas, implement targeted interventions, and assess the effectiveness of urban noise policies. It thereby enhances citizens' quality of life through more sustainable and responsive city planning.

***B.* Traffic Management** –
Traffic congestion is a major source of urban noise pollution. The system can identify noise-intensive zones, peak traffic hours, and high-exposure corridors using spatiotemporal data analytics. Transportation authorities can use this insight to optimize signal timings, plan alternative routes, and design low-noise traffic systems. Furthermore, predictive modeling can forecast noise variations during specific time intervals or public events, allowing for proactive noise control and improved urban mobility strategies.

***C.* Public Health** –
Excessive noise exposure has direct physiological and psychological effects on human health. The proposed system can generate early alerts and long-term exposure profiles for areas exceeding permissible decibel limits. Public health departments can leverage these insights to assess risk zones, design preventive campaigns, and conduct epidemiological studies linking noise exposure to cardiovascular or cognitive disorders. Such integration of noise analytics into healthcare systems promotes preventive medicine and informed policymaking.

***D.* Urban Planning** –
Urban planners can utilize the system's geo-referenced acoustic datasets to design noise-resilient infrastructure. Noise maps can inform land-use planning, zoning regulations, and placement of residential or educational institutions. The insights can also guide the construction of noise barriers, green buffers, and acoustic shields in critical zones. Incorporating this data into planning ensures environmentally conscious city layouts aligned with sustainable development goals.

***E.* Industrial Compliance** –
Industrial regions are among the leading contributors to environmental noise. The system provides automated monitoring and real-time compliance assessment aligned with environmental standards such as CPCB or ISO 1996. It can alert authorities and industries about threshold violations, generate compliance reports, and support the implementation of noise mitigation measures like enclosure systems or operational scheduling. This not only ensures legal conformity but also promotes corporate social responsibility and environmental stewardship.

***F.* Environmental Agencies** –
Regulatory bodies and environmental organizations can leverage the system's accurate, geotagged noise datasets for policy formulation, environmental audits, and public awareness initiatives. The generated maps provide reliable

evidence for legal enforcement and contribute to long-term databases useful for research and sustainable development planning. By offering real-time and historical analytics, the system strengthens transparency, accountability, and data-driven environmental governance.

Overall, the proposed system serves as an interdisciplinary framework combining IoT, data analytics, and environmental science to tackle one of the most underestimated urban challenges — noise pollution. Its deployment can accelerate progress toward smarter, healthier, and more sustainable cities, aligning with the United Nations' Sustainable Development Goals (SDGs) 3 (Good Health and Well-being) and 11 (Sustainable Cities and Communities).

VIII. FUTURE WORK

The present work has primarily focused on the design and implementation of an IoT-based framework for real-time noise monitoring and visualization. While the system has successfully demonstrated the feasibility of low-cost environmental noise mapping, several future enhancements are envisioned to extend its functionality and practical deployment.

1. **Deep Learning Integration:**

Future work includes the incorporation of advanced predictive algorithms, particularly Long Short-Term Memory (LSTM) and convolutional neural networks (CNNs), to forecast noise pollution trends based on historical datasets. These models will enhance the system's accuracy in identifying temporal and seasonal variations in noise levels.

2. **Sound Source Classification:**

Machine learning-based classification models will be developed to differentiate between various sound sources such as traffic, industrial machinery, construction, and human activities. This will enable a more granular understanding of the origin and intensity of noise pollution in different environments.

3. **Scalability and Deployment:**

The system can be expanded to cover larger geographical regions through a distributed network of IoT sensor nodes, enabling city-wide noise mapping and interconnected monitoring zones. Such scalability will facilitate cross-regional comparison and long-term environmental studies.

4. **Policy and Planning Support:**

Future iterations will focus on integrating advanced data visualization dashboards for urban planners and policymakers. These tools will assist in designing and evaluating noise mitigation strategies, developing zoning regulations, and ensuring compliance with environmental standards such as CPCB guidelines.

Collectively, these advancements will transform the current system into a comprehensive decision-support platform for sustainable urban management and smart city development.

IX.CONCLUSION

The present research demonstrates the successful design and implementation of a low-cost, IoT-enabled Noise Mapping and Prediction System aimed at addressing the growing issue of urban noise pollution. Through the seamless integration of sensor nodes, cloud-based data transmission, and visualization dashboards, the proposed framework provides an efficient mechanism for continuous, real-time noise monitoring. The system not only captures noise intensity across various urban locations but also visualizes this data through an interactive web interface, facilitating data-driven insights for researchers, policymakers, and city administrators.

The experimental results validate the system's ability to accurately sense, transmit, and display environmental noise data using cost-effective hardware components. Furthermore, the architecture's modular design ensures scalability, making it adaptable for large-scale smart city deployments. The combination of IoT technologies, Python-based analytics, and machine learning algorithms forms a robust backbone for environmental intelligence, offering a balance between technological feasibility and practical applicability.

In addition, the groundwork laid in this study paves the way for predictive noise analytics using advanced deep learning techniques. Integrating models such as Long Short-Term Memory (LSTM) networks will enable accurate forecasting of noise trends, aiding in proactive decision-making for urban planners. Beyond monitoring, the system holds immense potential for source classification—distinguishing between traffic, construction, industrial, or crowd-generated noise—thereby enhancing the granularity of environmental assessments.

The research also emphasizes user engagement and accessibility through the development of a prototype mobile application, designed to provide individuals with personalized noise exposure insights and location-based alerts. Such extensions bridge the gap between environmental sensing and public awareness, promoting citizen participation in noise management initiatives.

Future efforts will focus on expanding the sensor network to cover larger geographical areas, integrating AI-driven analytics for intelligent decision support, and linking the system with municipal databases to aid in regulatory compliance and policy formulation. Ultimately, this study contributes to the broader vision of sustainable smart city ecosystems, where IoT-driven intelligence and environmental consciousness converge to create healthier, quieter, and more livable urban spaces.

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