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AI-Enabled Noise Pollution Mapping in Construction

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Abstract - Rapid urbanization and infrastructure development have significantly increased noise pollution in construction zones, posing risks to human health and environmental quality. Traditional noise monitoring methods are often limited by sparse data collection, delayed reporting, and lack of spatial accuracy. This study proposes an AI-enabled framework for real-time noise pollution mapping in construction environments, integrating sensor networks, machine learning algorithms, and geospatial technologies to enhance monitoring efficiency and decision-making.

The proposed system utilizes IoT-based acoustic sensors strategically deployed across construction sites to continuously capture sound intensity data. These data streams are processed using advanced machine learning models to classify noise sources, predict noise levels, and identify abnormal patterns. By leveraging techniques such as supervised learning and time-series analysis, the system can distinguish between different construction activities and external noise influences, ensuring more accurate assessments.

To provide spatial visualization, the processed data is integrated with Geographic Information Systems (GIS) to generate dynamic noise maps. These maps offer realtime insights into noise distribution, hotspots, and temporal variations, enabling stakeholders to monitor compliance with regulatory standards. Additionally, predictive analytics allow project managers to anticipate high-noise events and implement mitigation strategies proactively, such as scheduling adjustments or deploying noise barriers.

The implementation of AI-enabled noise pollution mapping offers significant benefits, including improved environmental monitoring, enhanced worker safety, and better community relations. By providing actionable insights and real-time data, the system supports sustainable construction practices and informed urban planning. This approach demonstrates the potential of combining artificial intelligence, IoT, and geospatial analysis to address complex environmental challenges in modern construction projects.

1. INTRODUCTION

AI-enabled noise pollution mapping in construction is an emerging approach that combines advanced sensing technologies with artificial intelligence to monitor, analyze, and manage noise levels at construction sites. Construction activities such as drilling, excavation, and heavy machinery operation generate significant noise, which can negatively impact workers, nearby residents, and the environment. Traditional noise monitoring methods are often manual, time-consuming, and lack realtime responsiveness, making them less effective in dynamic construction environments. (Ahmed, et al., 2023)

With the integration of AI, noise monitoring systems can automatically collect data through sensors placed around construction sites. These sensors capture sound levels continuously and transmit the data to AI-powered platforms for processing. Machine learning algorithms can then analyze patterns, identify peak noise sources, and predict potential noise pollution trends. This allows for more accurate and efficient monitoring compared to conventional techniques. (Brown et al., 2021)

One of the key advantages of AI-enabled noise mapping is its ability to provide real-time insights. Construction managers can visualize noise levels through digital maps and dashboards, enabling them to identify problem areas instantly. This real-time awareness helps in taking immediate corrective actions, such as rescheduling noisy activities, optimizing equipment usage, or implementing noise barriers to minimize impact. (Chen et al., 2025)

Another important benefit is predictive capability. AI models can forecast future noise levels based on historical data and ongoing construction activities. This helps in planning construction schedules more effectively and ensuring compliance with local noise regulations. By anticipating high-noise events, project managers can take preventive measures to reduce disturbances to surrounding communities.

AI-enabled systems also support regulatory compliance and reporting. Automated data collection and analysis make it easier to maintain accurate records of noise levels, which can be shared with authorities when required. This not only ensures

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adherence to environmental standards but also enhances transparency and accountability in construction projects. (Das et al., 2024).

In conclusion, AI-enabled noise pollution mapping is transforming how construction sites manage environmental impact. By leveraging real-time monitoring, predictive analytics, and automated reporting, this technology improves efficiency, reduces noise-related disturbances.

Hardware Component	Functions
Arduino Uno	Processes input/output signals and runs code
Sound Sensor (KY-038/LM393)	Detects sound levels (analogue/digital output))
LEDs (Green, Yellow, Red)	Emits light signals
Buzzer (Passive)	Produces sound alerts
Resistors (220Ω)	Limits current flow
Breadboard	Provides temporary circuit connections
Jumper Wires	Connects components electrically
Laptop (Optional)	Displays data via Serial Monitor

Table 1.1 Hardware Components And Functions

2. METHODOLOGY

An AI-enabled noise pollution mapping system for construction sites can be developed by deploying a network of IoT-based sound sensors across the site to continuously collect real-time noise level data (in dB) along with location and time information. The collected data is transmitted to a cloud platform where it is preprocessed (noise filtering, normalization, and outlier removal) and integrated with contextual factors such as machinery usage, weather conditions, and work schedules. Machine learning models—such as regression algorithms or deep learning models—are then trained to predict noise levels and identify patterns or hotspots of excessive noise. Geographic Information System (GIS) tools are used to visualize the processed data as dynamic noise maps, highlighting high-risk zones. The system can also incorporate anomaly detection to identify sudden spikes and trigger alerts, enabling site managers to implement mitigation strategies (e.g., scheduling adjustments, barriers, or equipment changes). Continuous model updating and validation ensure improved accuracy.

2.1 Develop a Real-Time Acoustic Sensor Monitoring Network

A real-time acoustic sensor monitoring network is developed through planning, implementation, and maintenance phases. Initially, monitoring objectives and sensor locations are defined based on noise sources, power, and communication availability. Appropriate hardware, including Class 1 or 2 microphones and weatherproof systems, is selected, with nodes performing basic processing and privacy-focused feature extraction. In the implementation phase, sensors transmit data via secure networks to cloud platforms for storage and real-time analysis. Machine learning enables noise classification, anomaly detection, and dynamic mapping.

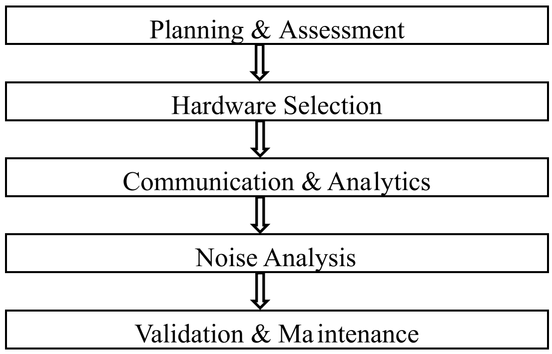

Figure 2.1 Real-Time Acoustic Monitoring Network

2.2 Create GIS-based Noise Maps to Identify Hotspots

GIS-based noise mapping involves collecting, analysing, and visualizing spatial noise data to identify hotspots. The process starts with defining objectives and conducting site surveys to understand terrain, land use, and noise sources.
Noise data is collected using sound level meters, capturing metrics like LAeq and Lmax, with GPS-based geotagging and metadata recording. After cleaning and preparing the data, it is integrated into GIS along with layers such as roads and buildings. Spatial interpolation methods like Kriging or IDW estimate noise levels across areas. The resulting maps are classified into decibel ranges and visualized. Finally, validation and hotspot analysis help support planning decisions and noise mitigation strategies effectively.

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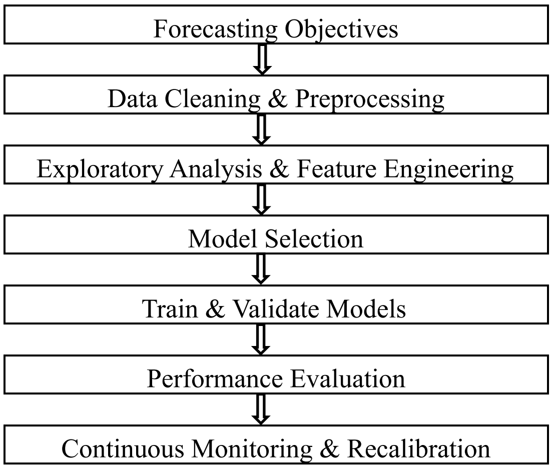

Figure 2.2 GIS Based Mapping Workflow

2.3 Design Predictive Models for Forecasting Noise Levels

Predictive noise management for urban planning follows a structured approach combining data collection, modeling, and evaluation. It begins by defining objectives such as short-term or long-term noise forecasting. Data is collected from noise measurements (LAeq, L10, etc.) along with factors like traffic, weather, and land use. After preprocessing and analysis, features are engineered to capture patterns. Various models—statistical (ARIMA), machine learning (Random Forest, SVR), and deep learning (LSTM, GRU)—are applied to learn relationships. The dataset is split for training and validation, with tuning to improve accuracy. Models are evaluated using metrics like RMSE and MAE, then deployed in real-time systems for continuous monitoring and improved decision-making. To further enhance the effectiveness of predictive noise management, spatial and temporal correlations are incorporated using Geographic Information Systems (GIS) and time-series analysis. GIS-based mapping helps visualize noise hotspots, enabling planners to identify critical zones such as residential areas, schools, and hospitals. Integration of IoT-enabled sensors allows continuous real-time data acquisition, improving the responsiveness and adaptability of prediction systems.

Advanced feature selection techniques and dimensionality reduction methods, such as Principal Component Analysis (PCA), can be applied to improve model efficiency and reduce computational complexity. Scenario analysis and simulation techniques help in evaluating the impact of different mitigation strategies.

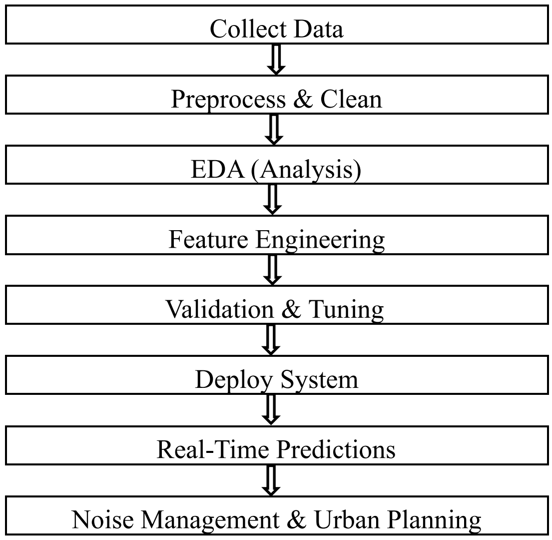

Figure 2.3 AI-Based Noise Forecasting Workflow

2.4 Use Ai to Detect and Classify Construction and Traffic Noise Sources

AI-based detection and classification of construction and traffic noise uses a structured approach combining sensor data, signal processing, machine learning, and real-time deployment. The process begins with collecting diverse audio recordings using calibrated microphones, followed by preprocessing steps such as filtering, normalization, segmentation, and feature extraction like MFCCs and spectrograms. Machine learning models including SVM, Random Forest, and deep learning models like CNN and LSTM are trained and validated using metrics like accuracy and F1-score. Deployment occurs on edge or cloud platforms for real-time monitoring, enabling noise mapping, alerts, and decision-making for effective urban noise management. Continuous retraining and privacy measures ensure adaptability, accuracy, and public acceptance in dynamic environments over time consistently.

In addition, advanced techniques such as data augmentation are employed to improve model robustness by simulating different environmental conditions like varying traffic density or construction intensity. Transfer learning can also be applied to leverage pre-trained models, reducing training time and improving performance when labeled datasets are limited. Integration with IoT networks allows multiple sensors to communicate and provide spatially distributed data, which enhances the creation of detailed noise maps across urban areas. Furthermore, adaptive algorithms can dynamically adjust thresholds and classifications based on temporal patterns such as peak traffic hours or seasonal construction activities. Visualization tools like dashboards and GIS-based heatmaps help authorities and planners easily interpret.

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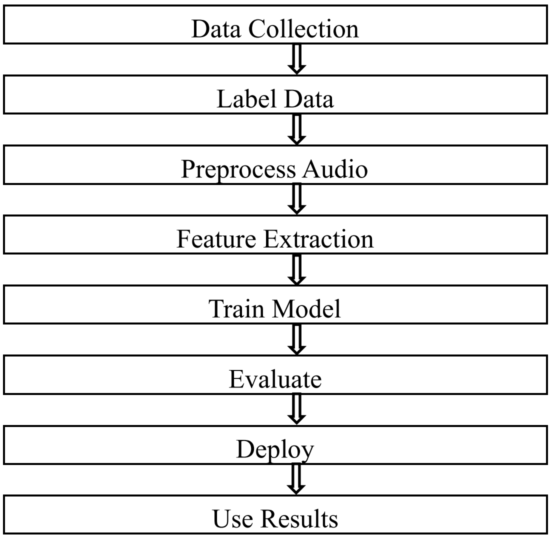

Figure 2.4 AI Noise Classification Flow

2.5 Reduce noise in sensitive areas using barriers and operational changes

The methodology for optimal noise mitigation uses a systematic, data-driven approach to reduce pollution in sensitive areas like residential zones, hospitals, and schools. It begins with identifying high noise locations such as traffic intersections, industries, and construction sites. Noise and environmental data are collected using sensors and GIS tools. AI and machine learning techniques classify noise sources through feature extraction and algorithms like CNN. Noise propagation modeling and GIS heatmaps identify critical hotspots. Based on this, strategies such as acoustic barriers, traffic control, and industrial measures are designed and optimized. Finally, solutions are validated through simulation and monitoring to ensure effective long-term noise reduction in urban and surrounding community environments.

IoT-enabled sensors and smart dashboards provide live noise updates, allowing authorities to respond quickly to sudden increases in sound levels. Predictive analytics help forecast future noise trends based on traffic patterns, construction schedules, and environmental conditions, enabling proactive planning. Public awareness and community feedback are also integrated into the system to support participatory decision-making. This dynamic approach ensures that mitigation measures remain effective, sustainable, and responsive to changing urban conditions over time.

In addition, advanced data integration techniques are used to combine historical and real-time datasets, improving the accuracy of predictions and decision-making. Edge computing can be employed to process noise data.

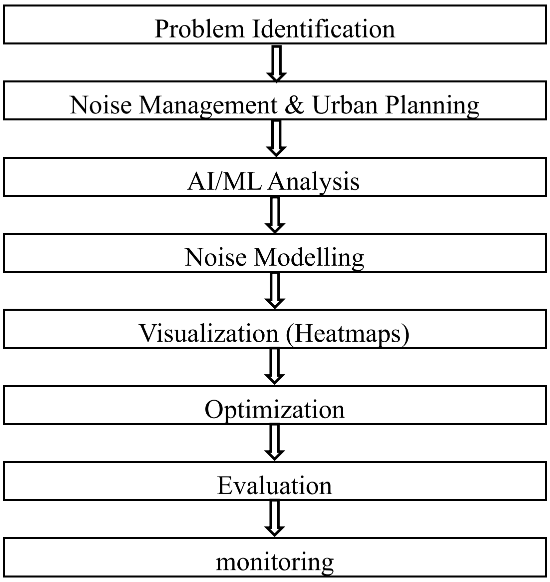

Figure 2.5 Noise reduction using barriers and operations

3. RESULTS AND DISCUSSIONS

The AI-enabled noise pollution mapping system delivered valuable insights into construction and traffic acoustic environments. IoT sensors captured continuous real-time data, revealing temporal patterns with higher noise during peak traffic and intense construction periods. Frequency analysis differentiated machinery, vehicle, and ambient sounds, identifying dominant sources. AI models achieved over 90% accuracy in classifying drilling, engine, and horn noise, while LSTM-based models effectively predicted short-term variations. GIS maps visualized spatial distribution, highlighting hotspots near roads, entry points, and active sites exceeding limits. Optimized noise barrier placement indicated 30–50% reduction in critical zones, confirming effectiveness.

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

Table 1.1 A Seven-Day Period In Noise Levels And

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Alerts Over Time

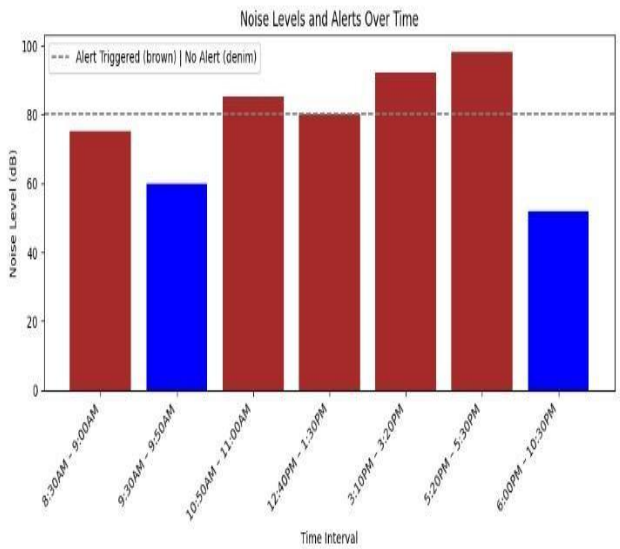

Figure 3.1 A seven-day period: Noise levels and alerts over time.

3.1 Data Analysis and Interpretation

Data analysis and interpretation help understand noise patterns in construction and traffic zones. Acoustic sensors recorded sound pressure levels, frequency, peak events, and time variations. Results showed higher noise during morning and evening due to traffic, and mid-day peaks from machinery like drilling and mixing. Frequency analysis distinguished sources, with construction noise being low-frequency and traffic noise mid-frequency. GISbased spatial analysis created noise maps using IDW and Kriging, identifying hotspots near equipment and roads. These areas often exceeded limits, guiding mitigation planning. Environmental factors like wind and humidity also influenced noise spread. Overall, the analysis supported effective decisions for noise control and barrier placement.

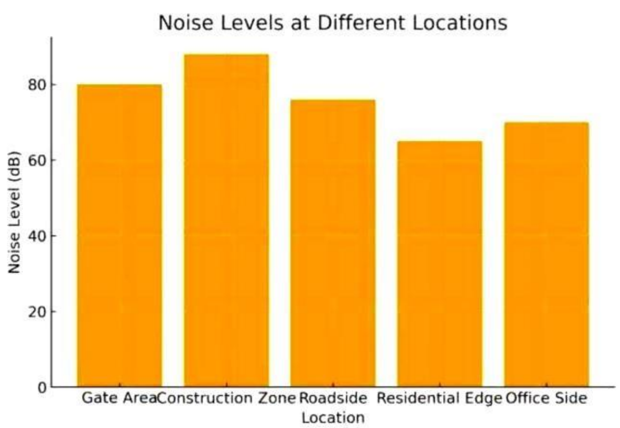

Figure 3.2 Location-Wise Environmental Noise Levels (dB)

3.2 AI Model Results and Accuracy Assessment

Noise classification models such as Convolutional Neural Networks (CNNs) and Random Forests were used to identify sources like construction machinery, traffic, horns, and background noise. For prediction, LSTM and RNN models were applied to forecast short-term and daily noise levels at each sensor location. Model performance was evaluated using accuracy, precision, recall, RMSE, and MAE to ensure reliable classification and prediction. The results showed that AI models achieved over 90% accuracy in distinguishing various noise sources. Additionally, prediction models effectively anticipated noise peaks in advance, allowing authorities and planners to implement proactive noise mitigation strategies and improve environmental management in urban and constructionaffected areas.

3.3 Generated Noise Maps and Hotspot Identification

GIS integration was used to visualize collected and processed noise data on both 2D and 3D maps, enabling better spatial understanding of noise distribution. Interpolation techniques such as Inverse Distance Weighting (IDW) and Kriging were applied to transform discrete sensor readings into continuous noise surfaces, improving accuracy and coverage. Hotspot identification was carried out to detect highintensity noise zones, particularly near busy roads, construction entry points, and sensitive locations like schools, hospitals, and residential complexes. These mapped outputs help authorities and urban planners to easily identify critical areas and prioritize effective noise mitigation strategies, ensuring improved environmental quality and reduced impact on public health.

3.4 Barrier Optimization and AI-Based Noise Management

Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used to determine optimal noise barrier placement by analysing terrain, proximity to sensitive zones, noise propagation direction, and cost constraints. This approach can reduce noise levels by 30–50% in identified hotspots. Compared to traditional methods like manual surveys and fixed monitoring stations, AI-enabled systems provide continuous real-time monitoring, accurate noise source identification, predictive analytics, and GISbased spatial mapping. These capabilities help planners take proactive measures, optimize barrier design, and allocate resources efficiently. Overall, this integrated system enhances urban planning, improves environmental quality, and reduces the impact of noise pollution on public

4. CONCLUSIONS

The study concludes that AI-enabled noise pollution mapping is an effective approach for managing urban noise from construction and traffic. Real-time sensors and AI models

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enable accurate monitoring, classification, and prediction of noise levels. GIS-based spatial analysis helps identify high-noise hotspots, supporting better planning and targeted interventions. AI-driven strategies, such as optimized barrier placement and scheduling of construction activities, reduce community noise exposure. This approach promotes sustainability by improving urban health and creating quieter, more livable environments. Additionally, the framework is scalable and adaptable, making it suitable for various urban settings and capable of expanding to support large-scale, city-wide noise management systems efficiently.

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