



NOISE POLLUTION DUE TO URBANIZATION USING ARTIFICIAL INTELLIGENCE

B.Pavani¹, K. Sai Nihaal Reddy², R. Pratyusha³, V.Janardhan⁴, M.Padmaja⁵
Civil Engineering Department, Mahatma Gandhi Institute of Technology, Hyderabad

Abstract

Rapid urbanization has intensified environmental noise through increasing road traffic, construction, commercial activity, rail transport and the concentration of people and infrastructure. Conventional noise surveys provide important measurements but may not capture the fine-scale, rapidly changing patterns of exposure across a city. Artificial intelligence (AI) offers opportunities to combine acoustic sensors, traffic data, weather observations, land-use information and geographic information systems (GIS) to classify sound sources, predict noise levels, identify hotspots and support targeted mitigation. This article reviews the relationship between urbanization and environmental noise and proposes an AI-enabled framework for continuous monitoring and decision support. Relevant research indicates growing use of machine-learning models for traffic-noise prediction and urban sound mapping, while also highlighting issues of data quality, geographic transferability and validation. The proposed framework consists of sensor deployment, data quality control, feature extraction, model development, spatial mapping, risk prioritization and evaluation of interventions. Potential models include random forest, gradient-boosting methods, support vector regression, artificial neural networks and deep-learning approaches for audio classification. The article emphasizes that AI should complement—not replace—calibrated sound-level measurements, acoustic principles and community engagement. Privacy, algorithmic bias, maintenance costs and unequal sensor coverage require explicit attention. A phased implementation suitable for rapidly growing

cities, including Indian urban contexts, is outlined. The framework can help urban authorities move from occasional measurement toward evidence-based, responsive noise management. As this is a review and conceptual article, it does not claim new field measurements or model-performance results.

Keywords: Urbanization; noise pollution; artificial intelligence; machine learning; urban sound mapping; traffic noise; smart cities; GIS.

1. Introduction

Urbanization transforms land use, transport networks, building density and patterns of economic activity. These changes create social and economic benefits, but they can also increase exposure to unwanted sound. Urban environmental noise arises from road traffic, railways, aircraft, construction, industrial operations, generators, public-address systems and commercial or recreational activities. In many cities, several sources overlap, and their contribution varies by hour, season, street geometry and weather. As a result, noise is not simply a matter of a city-wide average: residents may experience very different conditions within short distances.

Environmental noise is associated with annoyance, sleep disturbance and effects on wellbeing; evidence reviews have also considered cognitive and cardiovascular outcomes [1–3]. The World Health Organization's European regional guidance recommends reducing average road-traffic noise exposure below 53 dB Lden and night-time exposure below 45 dB Lnight, based on the health evidence reviewed for those guidelines [1]. These are exposure-guideline values for the specified indicators and should not be interpreted as a universal legal limit for every

country or noise source. The European Environment Agency's 2025 assessment likewise identifies transport noise as a major environmental health concern in Europe [4].

Monitoring systems commonly use sound-level meters, short-term field surveys, traffic counts and propagation-based noise maps. These tools remain essential, but sparse monitoring stations and infrequent surveys can miss local hotspots, short-duration peaks and changing traffic conditions. AI can add value by learning relationships between sound measurements and explanatory variables, detecting sound events, forecasting levels and helping direct field inspections. A review of AI-based traffic-noise prediction found that traffic flow and vehicle speed were among the most commonly used predictors in the studies examined [5].

This article has three objectives: (i) explain how urbanization contributes to environmental noise; (ii) review practical AI applications and their limitations; and (iii) propose an integrated framework for AI-assisted urban noise monitoring and mitigation. It is a narrative review and conceptual framework, not an original experimental study.

2. Urbanization and the Sources of Noise Pollution

2.1 Transport growth and congestion

Road traffic is a persistent source of urban noise because engines, tyre-road interaction, braking, acceleration and horn use occur repeatedly across the day. Congestion can produce stop-start driving and frequent acceleration, while heavy vehicles can contribute disproportionate sound energy. Motorcycles, buses, delivery vehicles and emergency vehicles have different acoustic signatures. Traffic volume alone is therefore insufficient: speed, vehicle class, road surface, gradient, intersection design and driving behaviour also influence measured noise.

2.2 Construction and changing land use

Construction associated with housing, roads, metro systems and commercial development can create intermittent high-noise periods from excavation, drilling, demolition, concrete work and material handling. Dense mixed-use development may place homes, schools and hospitals close to transport corridors or commercial activity. Building height, street-canyon geometry, façade materials and barriers

can change sound propagation and reflection. The effect of urbanization is consequently shaped by both the intensity of sound generation and the spatial arrangement of buildings and sensitive receptors.

2.3 Commercial, industrial and neighbourhood sources

Markets, restaurants, loading areas, workshops, power generators, public events and amplified music may contribute to local noise. These sources can be highly time-specific and may not be represented accurately by traffic-only models. A useful monitoring programme should distinguish source types rather than treating every high sound level as road traffic. AI-based acoustic event classification can support this distinction, provided that the model is validated for the local soundscape.

2.4 Unequal exposure

Noise exposure can vary according to housing quality, proximity to major roads, access to quiet open space and the ability to keep windows closed. A city-wide average can conceal neighbourhoods with repeated high exposure. Mapping should therefore report uncertainty and examine whether monitoring locations adequately represent residential areas, schools, hospitals, informal settlements and other sensitive locations.

3. Artificial Intelligence for Urban Noise Management

3.1 Monitoring and sound-event classification

Low-cost acoustic sensors can collect sound-level indicators at frequent intervals, while calibrated sound-level meters provide reference measurements. AI models can classify audio into broad categories such as road traffic, horn events, construction, aircraft, rail and human activity. Convolutional neural networks can learn patterns from spectrograms, while simpler classifiers can use engineered features such as spectral energy, temporal variation and event duration. Audio should be processed in ways that minimize collection or retention of identifiable speech; environmental monitoring generally does not require storing intelligible conversations.

3.2 Predicting noise levels

Supervised machine learning estimates a target such as equivalent continuous sound level (L_{eq}) from inputs including traffic volume, average

speed, heavy-vehicle share, time of day, road type, distance to road, building form, weather and recent acoustic readings. Candidate methods include multiple linear regression as a baseline, random forest, gradient boosting, support vector regression and artificial neural networks. Deep-learning methods may be useful where large, representative datasets are available. Recent reviews report broad use of neural networks and Leq in machine-learning studies of acoustic-environment quality [6].

Model selection should be based on validation performance, interpretability, computational requirements and the cost of errors—not on novelty alone. A complex model may offer little benefit over a well-calibrated baseline if data are sparse or noisy. Hybrid models that combine acoustic propagation principles with machine learning are promising because they can use physical knowledge while adapting to local conditions [7].

3.3 GIS-based noise mapping and hotspot detection

A geographic information system can combine sensor readings and AI predictions with roads, buildings, land use, population distribution and sensitive locations. The result is a time-aware noise map that can show typical daytime conditions, night-time exposure, event frequency and uncertainty. Mobile measurements collected along walking or cycling routes may increase spatial coverage. Research on mobile surveys and machine learning suggests that conventional noise maps may miss important street-level variation and some frequency-specific sound patterns [8].

Hotspots can be identified using repeated exceedances of locally applicable criteria, high predicted exposure, frequent peak events or proximity to sensitive receptors. A hotspot should not be labelled solely because of one unverified reading. Sensor calibration, minimum observation periods and confidence intervals are important to avoid misleading maps.

3.4 Forecasting and decision support

Time-series models can forecast short-term noise changes from traffic patterns, planned road closures, construction schedules or recurring events. Decision-support systems can compare potential actions such as traffic calming, rerouting heavy vehicles, speed management, quieter road surfaces,

construction-hour controls, barriers, building insulation and green or open-space design. AI can estimate where interventions may be most useful, but the actual effect should be confirmed through before-and-after measurements and consideration of possible noise displacement to neighbouring streets.

4. Proposed AI-Based Methodology

A practical research design for a rapidly growing city can be organized into seven stages. The design below is proposed for future field implementation; it is not presented as completed fieldwork.

Stage 1: Study-area selection and sampling

Select contrasting urban zones such as a major traffic corridor, a commercial district, a construction-influenced neighbourhood, a residential street and a quiet reference area. Sampling should cover weekdays and weekends, peak and off-peak periods, and both day and night where permitted. Record site characteristics and explain why each site was selected.

Stage 2: Data collection

Collect calibrated sound-level readings (for example, Leq and maximum level where appropriate), time stamps and GPS coordinates. Record traffic volume by vehicle class, average speed, road type, distance to junctions, construction activity, weather and nearby land use. Low-cost sensors may provide high-frequency coverage, but a subset of observations should be checked against a calibrated reference instrument. Follow applicable national and local rules for monitoring and occupational or environmental sound.

Stage 3: Data quality and feature engineering

Remove or flag invalid readings, instrument faults, missing time stamps and periods affected by sensor handling. Document calibration and sensor placement. Derive meaningful predictors such as hourly traffic count, heavy-vehicle proportion, time category, distance to road, building density and lagged sound levels. If audio is used, convert it to privacy-preserving features or short event labels where possible. Avoid retaining raw audio longer than necessary.

Stage 4: Model training and validation

Split data into training, validation and test sets by location or time block rather than randomly

mixing nearly identical adjacent samples. This reduces data leakage and tests whether a model can generalize to unseen places or periods. Train a simple regression baseline and compare it with random forest, gradient boosting and an ANN. For sound-source classification, report class-wise precision, recall and F1-score. For noise-level prediction, report MAE, RMSE and R^2 , alongside residual plots and performance by neighbourhood and time period. Hyperparameters should be selected using training/validation data only.

Stage 5: Spatial prediction and uncertainty

Apply the selected model to suitable road segments or grid cells and display predicted noise levels in GIS. Maps should identify measured versus modelled locations, provide the time window and metric, and communicate uncertainty. Do not imply that a prediction is a direct measurement. Evaluate spatial bias and avoid extrapolating confidently into neighbourhoods that are unlike the training data.

Stage 6: Intervention prioritization

Rank potential interventions using a transparent set of criteria: expected reduction in exposure, number and vulnerability of people affected, feasibility, cost, implementation time and risk of shifting noise elsewhere. AI can assist with scenario comparison, but local authorities and affected communities should make final decisions. Prioritize preventive planning alongside technological monitoring.

Stage 7: Evaluation and continuous improvement

Repeat measurements after an intervention using comparable times and conditions. Assess change in noise indicators, complaints, traffic patterns and exposure at sensitive sites. Recalibrate sensors, retrain models when data distributions change, and publish methods and limitations. A dashboard should show recent readings, validated predictions, alerts and the status of corrective actions.

5. Expected Outcomes and Potential Benefits

If implemented and validated, the proposed framework could provide more detailed spatial and temporal information than occasional manual surveys alone. Expected outputs include: (i) a georeferenced dataset linking sound levels to traffic and land-use variables; (ii) a source-classification model for common

local sound events; (iii) an AI model that predicts noise levels for monitored and comparable locations; (iv) GIS maps of recurring hotspots and uncertainty; and (v) a prioritization tool for mitigation planning. These are expected deliverables, not measured outcomes of the present article.

For urban planners, integrated maps could support road design, zoning, transport planning and siting of schools or hospitals. Municipal teams could use alerts to inspect recurring hotspots and verify complaints. Researchers could compare noise patterns with urban form and traffic management strategies. Public-facing dashboards may improve transparency if they explain the measurement period, data quality and meaning of each indicator.

AI may also help identify source-specific patterns. For example, a rise in average sound level during peak traffic may require a different response from a cluster of short horn events or construction-related peaks. The model should inform the investigation, not automatically assign blame or issue penalties without verified evidence and a fair process.

6. Challenges, Ethics and Limitations

Data availability and representativeness are fundamental challenges. Sensors may be concentrated near major roads or affluent areas, leaving quieter streets and underserved neighbourhoods poorly characterized. Low-cost devices can drift, clip at high levels or respond differently to wind and rain. Models trained in one city may fail elsewhere because vehicle fleets, road surfaces, building forms and driving behaviour differ. The literature on traffic-noise prediction therefore points to the need for comparison with established empirical methods and careful validation [5,7].

AI systems can also produce false alarms or miss uncommon events. Model performance should be reported by source category and neighbourhood, not only as a single average. A model that performs well at the city centre may be unreliable in peripheral or newly developed areas. Periodic recalibration and independent test data are necessary.

Privacy is important where microphones are deployed in public places. Data collection should be limited to what is needed, with clear notice, access controls and retention rules. Whenever possible, process sound locally and retain aggregate levels or event labels rather

than intelligible audio. AI-generated maps should not be used to profile individuals or infer private behaviour.

Cost, maintenance and institutional capacity can limit implementation. Low-cost sensors reduce the barrier to deployment but do not remove the need for calibration, connectivity, data storage, trained personnel and long-term funding. The system should use open standards where practical and be designed to work during network outages. Community consultation can help identify relevant sound sources and ensure that monitoring priorities are not determined only by easily measured locations.

Finally, prediction is not pollution control. A dashboard alone does not reduce noise. Benefits depend on the availability of clear standards, enforcement, transport and land-use planning, funding for mitigation and evaluation of results. AI should be treated as a decision-support tool within a broader environmental-management programme.

7. Recommendations for Indian Cities

For Indian cities experiencing rapid growth, a phased approach is likely to be more feasible than deploying a dense sensor network immediately. First, select representative pilot locations and align indicators with applicable national and state requirements. Second, pair a modest number of calibrated reference measurements with lower-cost monitoring devices and traffic counts. Third, build a local dataset that includes two-wheelers, heavy vehicles, horns, road works and mixed-use street conditions. Fourth, compare transparent baseline models with machine-learning alternatives using location-based validation. Fifth, share findings with municipal engineering, traffic-police, planning and public-health teams.

The pilot should begin with practical questions: Which locations show repeated high noise? At what times do problems occur? Which sources are most likely responsible? Which low-cost intervention can be tested? After a pilot intervention, repeat the measurements and report both improvements and unintended effects. Such a cycle links AI outputs to actionable urban management rather than treating technological sophistication as the goal.

8. Conclusion

Urbanization increases the complexity of environmental noise through transport growth,

construction, dense land use and overlapping commercial activities. Traditional measurements and acoustic models remain necessary, but AI can extend their usefulness by classifying sound events, predicting noise levels, generating dynamic GIS maps and helping prioritize interventions. A robust system requires representative data, calibrated sensors, location-aware validation, uncertainty reporting, privacy protection and continuous evaluation. The most suitable model will depend on local data and decision needs; simple, interpretable approaches should be tested before adopting more complex deep-learning systems. For rapidly growing cities, the recommended pathway is a carefully evaluated pilot that connects monitoring to transport planning, construction management and community priorities. AI cannot replace effective regulation or physical noise-control measures, but it can make urban noise management more timely, targeted and evidence-based.

References

- [1] World Health Organization (WHO). (2018). Environmental Noise Guidelines for the European Region. Copenhagen: WHO Regional Office for Europe. <https://www.who.int/publications/i/item/9789289053563>
- [2] Clark, C., & Paunovic, K. (2018). WHO Environmental Noise Guidelines for the European Region: A systematic review on environmental noise and quality of life, wellbeing and mental health. *International Journal of Environmental Research and Public Health*, 15(11), 2400. <https://doi.org/10.3390/ijerph15112400>
- [3] Brown, A. L., & van Kamp, I. (2017). WHO Environmental Noise Guidelines for the European Region: A systematic review of transport noise interventions and their impacts on health. *International Journal of Environmental Research and Public Health*, 14(8), 873. <https://doi.org/10.3390/ijerph14080873>
- [4] European Environment Agency. (2025). Environmental noise in Europe 2025. EEA Report 05/2025. <https://www.eea.europa.eu/en/analysis/publications/environmental-noise-in-europe-2025>
- [5] The state-of-the-art in the application of artificial intelligence-based models for traffic noise prediction: A bibliographic overview.

- (2024). Cogent Engineering.
<https://doi.org/10.1080/23311916.2023.2297508>
- [6] Tong, E., Chen, Y., Bai, Y., Zhang, F., & Krafft, T. (2025). Application of machine learning in modeling the quality of acoustic environments: A review. *Environmental Modelling & Software*, 193, 106658. <https://doi.org/10.1016/j.envsoft.2025.106658>
- [7] Wang, H., Liang, H., Wu, Z., Hou, Q., & Mao, H. (2026). Road traffic noise prediction: A review of techniques, challenges and future directions. *Environmental Impact Assessment Review*, 120, 108468. <https://doi.org/10.1016/j.eiar.2026.108468>
- [8] Mobile surveys and machine learning can improve urban noise mapping: Beyond A-weighted measurements of exposure. (2021). *Science of the Total Environment*, 775, 145600. <https://doi.org/10.1016/j.scitotenv.2021.145600>
- [9] Yalçinkaya, M. A. (2026). An end-to-end deep learning pipeline for urban noise monitoring with spatiotemporal analysis. *Scientific Reports*, 16, Article 22532. <https://doi.org/10.1038/s41598-026-60186-6>