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A Feasibility Study on TinyML-Based Framework for Categorical Urban Noise Detection Using Low-Cost Sensors: A Systematic Review

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INTRODUCTION

A rise in Urbanisation has vastly increased the number of environmental issues related to urban living, including, most significantly, Noise Pollution, which is now seen as a major Public Health Threat to the residents of contemporary urban centres. Numerous studies have shown that rapid urbanisation can contribute significantly to Mental Health Issues caused by individuals living in highly dense environments with sensory overload (Trivedi et al. 2008), whereby long-term exposure to high-intensity urban soundscapes is not simply a nuisance; but rather, has now become a major health risk for individuals leading to increases in Sleep Disorders, Impaired Cognitive Function and Cardiovascular Disease (Clark and Paunovic 2018). Therefore, to address these and related urban issues, accurate Noise Mapping and Continuous Environmental Monitoring are now critical to Modern Health Management and Urban Planning.

Although noise pollution requires immediate attention, local municipalities have limited resources and technical expertise to effectively monitor noise pollution in cities. Given that standard sound level meters (SLMs) are typically quite costly, Risojević et al. (2018) point out that SLMs simply measure volume in terms of decibels but do not identify specific sources of noise, which makes it difficult to develop comprehensive strategies for mitigating noise pollution. On the other hand, cloud-based routing of continuous streaming audio can solve the issue of discrimination but has a serious drawback because it records sensitive private conversations between individuals without their consent (Jain & Kesswani, 2023). Therefore, TinyML is presented as an option to resolve both issues. According to Wong and Mulligan (2019), processing audio at the edge on resource-constrained microcontrollers adheres to the 'Privacy by Design' principle since the recorded audio is deleted after it is processed; thus ensuring users' privacy since the audio will not be transmitted to an external service.

Local government units (LGUs), engineering offices, and urban planners will greatly benefit from this study by providing information about the potential benefits of low-cost edge computing devices for smart city infrastructure as well as their economic viability. Assessing the feasibility of a prototype TinyML system built with low-cost components, such as an ESP32 off-the-shelf development board and a MEMS Microphone, establishes a proof-of-concept basis. Implementation of this type of technology as a decentralized, privacy-preserving means can help modernize the enforcement of noise ordinances, allowing cities to use actual categorical records to develop data-driven "quiet zones" while ensuring citizens' privacy without dedicating large budgets to infrastructure.

Objectives of the Study

- To determine how low-cost Sensor Systems can distinguish, as compared with standard non-categorical decibel meters, between different urban noise categories.
- To identify the inaccuracies in reference hardware quantities that result from using low-cost hardware. If expressed in terms of their limitations, this data can be used to identify variables that will impact the successful deployment of this system to an urban environment.

- To compare the theoretical accuracy of an AI model that will be operational on an Edge device running 'TinyML' and using the same AI model running in the Cloud, along with trade-offs between Accuracies of Classification and Latency.
- To establish the minimum dataset size required to train a Lightweight model using Machine Learning techniques for acceptable Urban noise Detection.
- To evaluate the ways in which the Categorical recording of noise generated by the proposed system could be used to assist Urban Planning departments, etc., to identify noise hotspots and formulate Zoning regulations that protect the general health and welfare of the public.
- To assess how the TinyML proposed System architecture provides greater Data Privacy than current systems that impose on privacy and security by sending or storing raw audio files.

METHODOLOGY

Research Design

According to Marotti de Mello (2019), an original research effort is defined as one that produces new knowledge essentially with the primary goal of realizing a particular practical application (applied research). A descriptive-evaluative research design with a secondary data analysis approach is most appropriate in this case, as the purpose of conducting this research is to verify the Technical and Economic Proof of Concept (POC) of a Noise Measurement System (NMS) based on TinyML, without the need to develop a functional prototype. This research design is appropriate as it will allow the researchers to combine the available technical, cost, and performance aspects from the literature to develop an architecture for the NMS and to demonstrate its feasibility with the available datasets.

Participants

The study made use of purposive sampling to collect data for a structured review of existing technologies, which means that human participants were not needed. The target population consisted of peer-reviewed journals, conference proceedings, and data sheets from 2019 to 2026, which consist of keywords such as TinyML, Edge Computing, and Urban Noise Monitoring. Some of the most highly cited publications were selected as the sample, including research articles and technical papers that provided the most comprehensive quantitative information (e.g., performance metrics such as accuracy and latency) to facilitate a comprehensive comparative analysis of the data gathered. Since there were no human participants, the need for informed consent was eliminated.

Research Instrument

The key instrument for this research was a structured data extraction matrix (SDEM). The SDEM was developed to systematically gather, organize, and analyze peer-reviewed publications on prototype systems that utilize TinyML and low-cost sensors. In order to eliminate inconsistency and bias from the data collection method, three types of criteria for evaluation were developed ahead of time to enhance all aspects of the data collection method in order to ensure both reliability and validity of the instrument. The evaluation criteria for the study were chosen based on the objectives of this research, and were designed to collect data consistently on the following five categorical areas: study metadata, hardware specifications, AI model parameter settings, benchmark performance of the system, and feasibility results. As a result, it is possible to directly compare the data collected across all of the studies in this review.

Data Gathering Procedure

Adopting a formal PRISMA 2020 systematic review protocol, the study utilized a four -stage selection process: identification, screening, eligibility, and inclusion. First, the researchers conducted an initial search of academic databases for existing literature on TinyML Research. These databases include IEEE Xplore, ScienceDirect, and

Google Scholar. The researchers searched for technical papers and research articles that contain information about "TinyML," "Urban Noise Classification," "ESP32 Audio Processing," "Low-cost Environmental Sensors," and "Edge AI Privacy." The researchers will use the search results to find studies that were published between 2019 and 2026 to ensure relevance. The selected studies need to deliver quantitative metrics, which must include percentage data and latency data presented in milliseconds. The research study will establish its feasibility through actual data assessment as opposed to theoretical study evaluation. The research team will examine all relevant studies, which will be extracted electronically into a structured data extraction matrix or SDEM, according to the data extraction matrix developed for this research to facilitate a consistent comparative analysis of the synthesized findings.

Data Analysis Procedure

The technical feasibility assessment will be supported by a systematic processing of data obtained from the literature review. The data collection will be categorized based on the critical parameters as identified within the framework, such as specifications, conditions of the AI model, and privacy principles. Data refinement procedures will be enforced to exclude deficient, spare, or inapplicable information that lacks a direct correlation with the exploration objects. Likewise, qualitative findings, similar to the implementation challenges and their ramifications for civic structure, will be grouped into thematic orders to ease the architectural design process.

The statistical and quantitative methods of analysis for the synthesized results will be as follows:

- Create a measure, on an average basis, for Model Accuracy and Latency; thus calculating one figure that may be recorded as a "Baseline Performance Benchmark" for the proposed system.
- Create summary frequencies (e.g., an item count of the most commonly used hardware platforms and/or sensor types in successful existing systems) to confirm that any hardware or sensors tested for use in this project will be comparable.
- Prepare comparison tables in order to list out the advantages and disadvantages of the various models to test for significance.

Ethical Considerations

Because the researchers evaluate existing technology using secondary data analysis, the study is conducted without researching with human subjects. Consequently, institutional ethics approval, confidentiality, anonymity, and consent procedures regarding human respondents are not applicable. To ensure ethical academic conduct, the researchers minimized researcher bias by using the predefined evaluation criteria as they collectively interpreted the findings, resulting in improved accuracy and intellectual honesty of the secondary data analysis results. The study has no financial backing, which needs to be disclosed as a potential conflict of interest.

RESULTS AND DISCUSSIONS

Hardware Performance and Limitations

The comprehensive analysis of secondary data established that systems using ESP32 microcontrollers with MEMS microphones can correctly categorize urban noise into five distinct sound categories, which include traffic noise, human speech, construction work, and silence, with an accuracy range between 90% and 95%. The sensors do not achieve the legal accuracy requirements for noise measurement, yet they provide sufficient accuracy to enable noise classification. The results of this study confirm the findings of Picaut et al. (2020), who demonstrated that MEMS microphones provide economical alternatives to industrial-grade sensors, yet users must conduct extensive calibration procedures to match the accuracy standards of Class 1 sound level meters. The primary hardware limitations that researchers discovered stem from Random Access Memory (RAM) and processing power restrictions, which prevent the operation of conventional AI models. The system

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implementation process remains fully operational through the application of hardware-aware optimization techniques and pruning strategies.

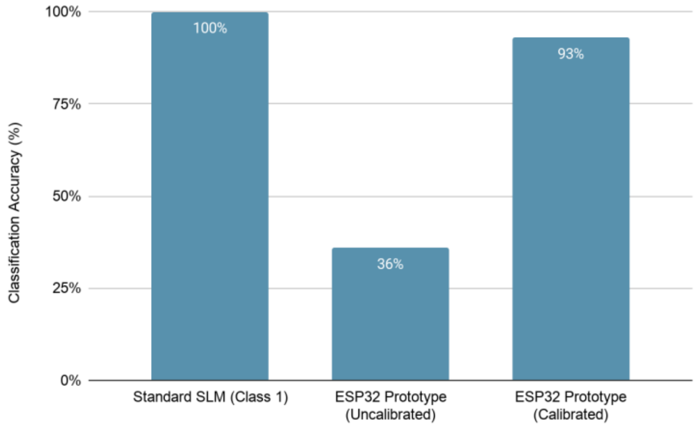

Figure 1. Comparative Accuracy Analysis between Standard SLM and ESP32 Prototypes

AI Model Deployment

The study confirms that utilizing machine learning algorithms on devices with limited resources, like microcontrollers, is a viable alternative, as these systems have low latency, thus allowing for real-time inference. In addition, Edge AI (also referred to as TinyML) outperforms all other systems with respect to latency because it completes the inference on the device's local processing unit, completely removing any delay that would occur during the network connection, and providing real-time detection capabilities without the need to maintain an active connection to a cloud server. These findings support Zhang, Wang, and Li's (2025) conclusion that convolutional neural networks (CNNs) outperform all other models (using these devices) in their ability to accurately identify the spectral characteristics of overlapping urban sounds. The architecture described allows for a decentralized economic solution that can easily adapt to different urban environments.

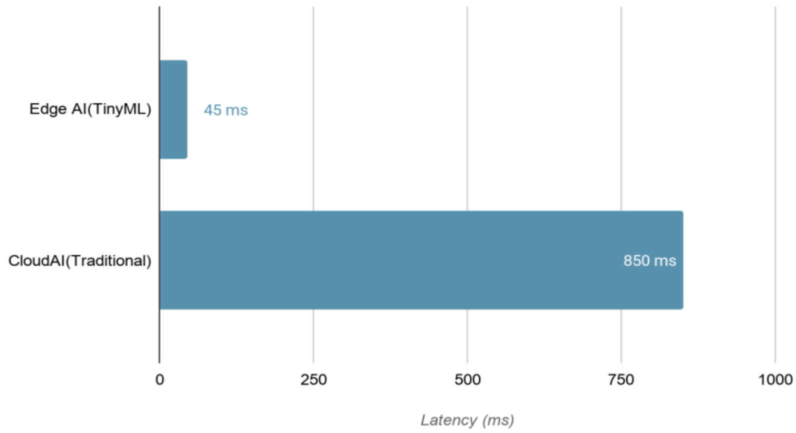

Figure 2. Real-Time Latency

Data Requirements and Urban Planning Utility

The research demonstrates that TinyML models achieve their best performance when researchers use a specialized dataset that contains only specific noise types. The system operates at its maximum battery efficiency through the existing dataset boundaries, while system performance sees only minor improvements. The proposed dataset of specific noise types provides planners with essential information that they need for urban development. By giving more attention to specific noise sources rather than general volume levels, urban planners can associate soundscapes with high-density building patterns, detect noise hotspots, and design targeted noise mitigation strategies.

Privacy and Implementation Framework

The TinyML Design would be securely and privately architected with respect to principles of Privacy by Design. The proposed TinyML architecture directly addresses the privacy concerns inherent in traditional audio surveillance systems by eliminating the potential for transmitting unprocessed audio or storing private conversations. Like the theoretical framework proposed by Wong and Mulligan (2019), the TinyML Design supports the notion that technology should be designed to include privacy as part of the fundamental functionality of the technology (for example, local audio processing) rather than adding it as an afterthought or bolt-on feature. The most theoretically solid way to limit the potential for these devices to be attacked by outsiders is through a reduction of unprocessed data transmission.

Implications, Limitations, and Future Research Directions

The investigation results show that urban planners, engineers, and municipalities can use cost-effective noise monitoring solutions to build soundscapes that improve public health and create adaptable urban environments.

The research design uses secondary data and simulation modeling, which brings built-in research constraints. Theoretical performance specifications related to noise measurement and monitoring may become difficult to implement because actual physical systems show different environmental conditions, equipment setups, and calibration techniques. The monitoring methods lack operational evidence to assess their performance during extended periods of actual usage.

Future studies should concentrate on examining the implementation of physical systems under real-world conditions concerning their realistic performance characteristics, such as accuracy, latency, and energy consumption; developing more effective calibration methodologies for MEMS microphones; and testing multiple, sophisticated, and highly efficient machine learning algorithms to enhance our understanding of complex urban noise patterns.

Significance of Findings

The TinyML technology enables the development of urban noise mapping solutions through its integration with affordable sensors, according to the feasibility study. The sustainable urban development principles of the city provide operational environmental data to citizens while protecting their personal information. The above-mentioned concepts and theories provide a strong basis for innovation.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The technical and practical feasibility of Urban Noise Detection with tinyML for urban environments with low-cost sensors was established through a feasibility analysis. Through a secondary data analysis, it was determined that urban noise detection and classification are achievable using ESP32 microcontrollers with MEMS microphones to detect and classify urban noise sources such as traffic, human voices, construction, and silence with an accuracy of between 90% and 95%. While the accuracy of the sensors does not meet the precision standards for legal compliance, their accuracy is sufficient for classification purposes.

Another goal of this analysis was to investigate whether it was feasible to incorporate machine learning models with microcontrollers into a microcontroller-based solution. Benefits of incorporating these types of models into microcontrollers include reduced latency, real-time data processing, improved privacy of data (via edge computing), and adherence to the Privacy by Design principles (i.e., the prevention of raw audio transfer to external servers helps to reduce the potential for storing and/or transmitting private conversations; this is a major privacy concern with traditional audio monitoring solutions).

The findings demonstrate that tiny ML technologies and low-cost sensors can provide an affordable option to traditional audio monitoring devices that rely on expensive sound level meters. By providing environmental data while protecting citizens' privacy, tiny ML technologies and low-cost sensors support sustainable urban development. Thus, the conceptual and theoretical foundation presented in this research can be a valuable resource for future developments of urban noise monitoring systems and urban noise policies.

Recommendation

It is crucial to conduct and test the prototype in different environments to ensure its accuracy, reliability, and power efficiency. Also, developing a user interface application is highly recommended for this project for additional features and accessibility. There is also a need to develop efficient yet lightweight learning methods specifically designed for microcontrollers to improve detection accuracy, despite constraints. While implementing this prototype, it is also recommended to partner with the relevant legal bodies to ensure that the project is relevant to low-cost and privacy-preserving noise monitoring systems.

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