

Abstract

Current gunshot detection systems like ShotSpotter suffer from high false positive rates and operational inefficiencies. This project explores alternative acoustic detection methods by developing custom sound libraries, applying machine learning models, and evaluating detection performance. The goal is to design a more accurate, reliable, and scalable sound-based gunshot detection solution. Through controlled dataset generation and comparative analysis of machine learning architectures, we seek to quantify the trade-offs between model complexity, detection latency, and classification accuracy. Special emphasis is placed on optimizing feature extraction pipelines and signal preprocessing stages to enhance robustness against environmental noise, multi-path reflections, and overlapping acoustic events.

Background

Gunshot detection systems use acoustic sensors and machine learning to identify firearm discharges in urban environments. These systems aim to:

- Reduce emergency response times
- Improve evidence collection
- Address urban gun violence

However, current technologies like ShotSpotter, deployed by the NYPD, exhibit critical limitations that undermine their effectiveness:

- **High False Positive Rate:** Most ShotSpotter alerts do not correspond to confirmed shootings.
- **Resource Waste:** Police are often dispatched unnecessarily, straining department resources.
- **Operational Concerns:** In some months, fewer than 10% of alerts resulted in confirmed gunfire.



Figure 1. Number of Confirmed Shooting Incidents vs. Total ShotSpotter Alerts by Month [7]

Objectives

- Study different acoustic gunshot detection approaches.
- Create custom gunshot sound libraries for training and testing.
- Evaluate machine learning-based classification versus threshold-based detection.
- Identify effective and efficient acoustic detection method.

Proposed Approach



Figure 2. End-to-End Process for Sound Detection System Optimization Using Machine Learning.

Our project focuses on evaluating and optimizing acoustic-based gunshot detection methods through a multi-stage process:

- **Custom Sound Library Development:** Generate and curate a custom dataset consisting of gunshot and non-gunshot acoustic events, using sound modeling software to simulate diverse urban environments.
- **Signal Preprocessing and Feature Extraction:** Preprocessing techniques such as filtering and normalization are applied to raw audio signals. Features like spectrograms and time-domain characteristics are extracted for machine learning analysis.
- **Machine Learning Methodology:** Machine learning models, such as convolutional neural networks (CNNs), are trained and evaluated to classify gunshot versus non-gunshot sounds based on the extracted features.
- **Performance Evaluation and Comparison:** Detection accuracy, false positive rate, and computational efficiency will be compared across different approaches to identify an optimal system design for real-world deployment.



Figure 3. Gunshot Detection Pipeline

The gunshot detection pipeline begins with **Sound Input**, where acoustic events are captured using microphone arrays. Captured audio is passed through a **Preprocessing** stage, where filtering, normalization, and noise reduction techniques are applied to improve signal clarity.

During **Feature Extraction**, audio signals are converted into mel-spectrograms — time-frequency representations that highlight distinct acoustic signatures.

These extracted features are fed into a **Machine Learning Classifier** designed to distinguish gunshot events from non-gunshot sounds such as fireworks, engines, and other urban noise sources.

Multiple machine learning approaches are being explored, including:

- **Convolutional Neural Networks (CNNs)** trained on spectrogram images.
- **CNN + LSTM hybrid models** to capture both spatial and temporal features.
- **1D CNNs on raw audio** to preserve detailed waveform information.
- **Transformer-based models** leveraging self-attention for advanced audio sequence recognition.

The system outputs a final **Gunshot Detection** decision, aiming to maximize detection accuracy while minimizing false alarms across varied acoustic environments.

In addition to sound classification, we are investigating **Time Difference of Arrival (TDoA)** techniques to localize the source of detected gunshots. TDoA algorithms use the difference in arrival times of an acoustic event across multiple spatially separated microphones to estimate the position of the sound source. By combining accurate classification through machine learning with precise localization via TDoA, the overall system can not only detect gunfire events but also determine their geographic origin, improving real-time response capabilities for law enforcement and public safety applications.

Sound Modeling

To design an accurate and reliable gunshot detection system, it is important to understand how acoustic signals behave across complex environments. Sound modeling software provides a powerful platform for simulating gunshots in varied conditions, allowing for controlled experimentation, data generation, and sensor optimization.

Synthetic Data Generation – The sound modeling software simulates gunshots in various acoustic environments, incorporating factors like echo, background noise, and distance variations.

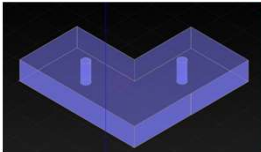


Figure 4. Modeled Test Environment Used for Creating the Custom Sound Library.

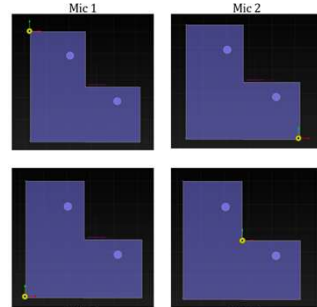


Figure 5. Optimized Microphone Placements Within the Modeled Room for Sound Library Development.

By simulating the propagation of sound waves within complex acoustic environments, the software enables precise optimization of microphone placement. This ensures maximum signal fidelity by enhancing direct path reception, minimizing multipath interference and echoes, and reducing the impact of environmental noise. The result is improved accuracy in gunshot localization and overall system robustness.

Our Proposed System



Figure 6. Proposed Gunshot Detection System

Our proposed system architecture consists of multiple acoustic sensing nodes, each built around an **ESP32 microcontroller** connected to an omnidirectional microphone. Each ESP32 node will incorporate a simple **volume detection circuit** to continuously monitor ambient sound levels. When a loud acoustic event exceeding a predefined threshold is detected, the ESP32 will locally execute a **gunshot detection algorithm** to classify the sound based on extracted features (e.g., using a lightweight machine learning model or a threshold-based classifier).

If the sound is classified as a potential gunshot, the ESP32 will immediately **time-stamp** the detection event and **transmit the time-stamp wirelessly** to a central **Raspberry Pi server** using a low-latency communication protocol (such as Wi-Fi or ESP-NOW).

The Raspberry Pi aggregates time-stamps from multiple ESP32 nodes and performs a **Time Difference of Arrival (TDoA) calculation** to estimate the location of the sound source. Upon localizing the event, the Raspberry Pi will **trigger an external camera module** to capture an image of the detected area, enabling visual documentation and potential evidence collection for situational awareness and post-event analysis.

Conclusions

This project aims to develop a **more efficient gunshot detection system** by:

1. Creating a custom sound library
2. Evaluating different machine learning models
3. Improving microphone placement
4. Optimizing the gun detection pipeline

For our **next steps**, we plan on doing the following:

1. Build and test a prototype
2. Expand synthetic testing
3. Refine machine learning models

References

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