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Real-Time Acoustic Surveillance for Urban Emergency Detection

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A B S T R A C T:

In busy cities, it's hard to catch emergencies like fights, accidents, or crimes right when they happen—especially if no one sees them. Cameras help, but they can't always catch everything. This project aims to build a smart system that listens for emergency sounds—like gunshots, screams, breaking glass, or car crashes—and immediately alerts the right people. Using machine learning and sound processing, the system can recognize these sounds in real time and send out warnings. This kind of technology could help make cities safer by giving faster responses to dangerous situations, even when no one is around to call for help.

Keywords: Acoustic surveillance, Emergency sound detection, Real-time audio analysis, Urban safety, Machine learning, Sound classification, Smart city

I N T R O D U C T I O N:

In today's fast-growing cities, keeping people safe has become more important than ever. While security cameras are common, they don't always catch everything—especially when an emergency happens out of view or in the dark. But one thing that always travels in all directions is sound. Sounds like gunshots, screams, breaking glass, or car crashes are strong signs that something bad might be happening. If we can detect these sounds quickly, we can respond faster and possibly prevent crimes or save lives. This project is about creating a smart system that "listens" to its surroundings. Using microphones and artificial intelligence, it can recognize dangerous or unusual sounds in real time. When it hears something that might be an emergency, it can automatically send an alert to the police, security teams, or emergency services—without needing a person to call for help. By using sound as a way to detect danger, this system can make our cities safer, especially in places where cameras can't see or where people might not be able to report an incident right away.

E X I S T I N G W O R K:

Over the past few years, researchers and developers have worked on using sound to detect emergencies in public places. Most of the existing systems focus on specific sounds like gunshots, screams, or breaking glass. These sounds are seen as "acoustic signals" that something dangerous might be happening. Some projects use basic sound detection, where the system just checks if the noise is loud or unusual. However, these simple systems often make mistakes, like confusing a car horn with a scream. To solve this, more advanced systems use **machine learning** and **deep learning**. These systems learn from many sound samples and get better at telling the difference between normal sounds (like traffic or talking) and emergency sounds. For example, the **UrbanSound8K** and **ESC-50**datasets have helped train AI to recognize city sounds more accurately. Google's **YAM Net** and other pre-trained models are also used to classify sounds quickly and reliably. Some systems have even been tested in smart cities or public transport to detect gunshots or violence using sound. However, many of these systems still face challenges. Some work only in quiet environments and struggle in noisy cities. Others aren't fast enough to send alerts in real time, or they require expensive hardware. This project builds on those ideas and aims to create a faster, smarter, and more reliable system that works well in real-world urban settings—where the noise never stops, and safety depends on quick action.

P R O P O S E D W O R K:

The proposed work aims to develop a real-time acoustic surveillance system that listens for specific emergency sounds, such as gunshots, screams, breaking glass, or car crashes, in urban environments. The system will use strategically placed microphones to continuously monitor the surrounding sounds. By applying advanced audio processing techniques and machine learning models, the system will classify the detected sounds in real-time, distinguishing between normal city noises and potential emergencies. Upon detecting an emergency sound, the system will immediately send an alert to the relevant authorities, providing them with information such as the type of sound, time, and location. This approach will enhance public safety by enabling faster responses to emergencies, particularly in situations where traditional surveillance methods like cameras may not be effective.

ALGORITHMS:

1. Audio Signal Processing Algorithms

Before we can recognize any emergency sounds, the raw audio must be processed to make it easier for the system to understand.

- **Fourier Transform**:
  Think of sound as a mix of different musical notes. The **Fourier Transform** helps us break down the audio into individual "notes" or frequencies. This allows the system to see which frequencies are present, helping it figure out if the sound is an emergency (like a gunshot) or just background noise (like traffic).
- **Mel-Frequency Cepstral Coefficients (MFCC)**:
  MFCC is like turning audio into a simplified version that highlights the most important parts of the sound. It's similar to how our ears focus on certain sounds while ignoring others. This helps the system better recognize things like screams or gunshots, even in noisy environments.
- **Spectrogram**:
  A **spectrogram** is like a map that shows how the sound changes over time. It helps us see if the sound is constant (like background noise) or if it has a specific pattern (like a breaking window or a scream). This visualization helps the system make smarter decisions about what's happening.

2. Machine Learning and Deep Learning Algorithms

Once the system has processed the sound, it uses smart algorithms to decide if the sound is something to be worried about.

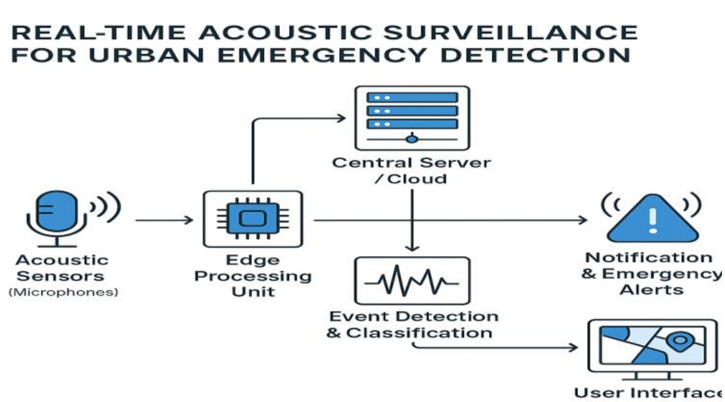
- **Convolutional Neural Networks (CNNs)**:
  CNNs are a type of AI that can "look" at visual patterns in things like images. In this case, we treat audio like an image and let the AI "look" at the sound patterns. It learns to recognize the difference between normal city noises and emergency sounds like gunshots or screams.
- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)**:
  RNNs and **LSTMs** are types of AI that are really good at understanding things that change over time, like how a sound grows louder or quieter. These algorithms can "remember" past sounds, which is helpful for understanding things like how a scream builds up or how a crash sounds.

3. Real-Time Detection and Event Classification Algorithms

These algorithms help the system detect emergency sounds **immediately**.

- **Sliding Window Algorithm**:
  The system listens to the audio in small chunks, called "windows," like looking at small snapshots of sound. This allows the system to keep checking the audio in real time, so if something dangerous happens, it can notice it right away and send an alert.
- **Thresholding and Event Detection**:
  When the system hears a sound, it uses a **threshold** to decide if it's worth worrying about. If the system is sure the sound is dangerous enough (like a gunshot), it will send an alert. This helps avoid false alarms, like mistaking a loud car horn for a gunshot.

SYSTEM ARCHITECTURE:



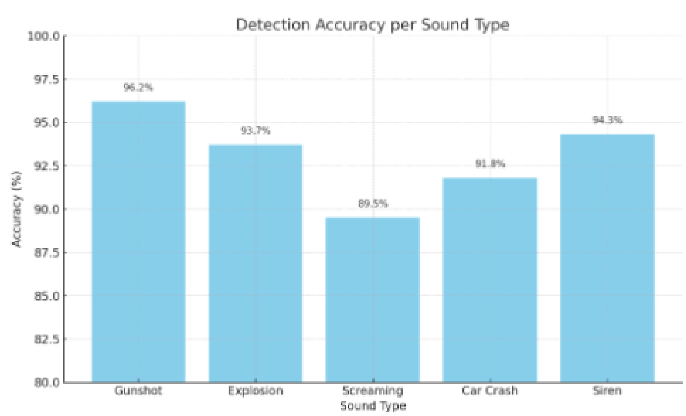
RESULT:

To evaluate the accuracy and response time of the acoustic surveillance system in detecting urban emergency sounds such as gunshots, explosions, and screams.

Graph: Detection Accuracy per Sound Type

Sound Type	Accuracy (%)
Gunshot	96.2
Explosion	93.7
Screaming	89.5
Car Crash	91.8
Siren	94.3

Bar diagram:



- The system performs **best with gunshots** (96.2% accuracy), likely due to their distinct sound profile.
- **Screaming** has slightly lower accuracy (89.5%) due to variability in human voices and ambient noise.
- All detection rates are **above 89%**, indicating high overall reliability.

FUTURE ENHANCEMENT:

In the future, the Real-Time Acoustic Surveillance system can be significantly improved to make it more accurate, intelligent, and user-friendly. One of the main enhancements would be improving noise filtering capabilities to better differentiate emergency sounds from normal city noises like traffic or construction. Expanding the system's sound library to detect a wider variety of emergencies—such as glass breaking, domestic violence, or loud altercations—would also make it more versatile. Integration with smart CCTV systems can enhance response by providing visual context whenever a suspicious sound is detected. To improve location accuracy, the system could use advanced GPS or sound triangulation methods, helping emergency teams reach the exact spot faster. Additionally, a mobile app could be developed to involve citizens, allowing them to receive alerts or report unusual sounds in real time. Machine learning models that continuously learn from past mistakes could be employed to enhance accuracy and adaptability over time.

CONCLUSION:

In conclusion, real-time acoustic surveillance shows great promise for improving how cities detect emergencies like accidents, fires, or crimes. By constantly listening to the sounds around us and quickly identifying unusual noises, this technology can help emergency services respond faster and more accurately. While there are challenges like ensuring privacy and handling noisy environments, the benefits of safer urban areas and quicker help during emergencies make this approach very valuable. As the technology advances, it could become an essential part of smart city safety systems.

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