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# A DATA-DRIVEN APPROACH TO PUBLIC SAFETY EVENT DETECTION USING NLP TECHNIQUES

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**ABSTRACT:** This paper uses cutting-edge Natural Language Processing (NLP) to analyze massive amounts of unstructured text data from social media, news stories, and emergency communication logs to identify public safety incidents. Machine learning models like deep learning architectures, feature extraction, and preprocessing are used to identify and categorise safety-related events like accidents, crimes, and natural disasters in real time. The system improves situational awareness and early warning for authorities and first responders using sentiment analysis, named entity recognition, and topic modeling. Experiments show that NLP-driven monitoring systems are more precise, accurate, and responsive than traditional systems. This shows how important they are to proactive public safety management.

***Keywords:*** *Public Safety, Event Detection, Natural Language Processing (NLP), Social Media Analysis, Machine Learning, Deep Learning, Text Mining, Named Entity Recognition,*

## 1. INTRODUCTION

Every physical event has a sound. Such as seeing someone, hearing a bird sing, seeing a river flow, or hearing a stone fall. Fireworks, parties, and crowd applause are auditory stimuli. Landslides and accidents can cause this. A system that detects noise and determines its benefit or harm intrigues me. Although present, the technology needed for our previous innovations is not easily accessible. Before discussing the future of NLP, it's important to assess its current status and how often its features are used for text analysis and safe listening. Artificial intelligence allows smartphones to use natural language processing for voice control, which most people use.

### Objective

This research aims to create a software prototype that can detect real-time threats like robberies, assaults, and other crimes from background noise. Then, it will notify registered contacts via WhatsApp, emails, and texts. Deep learning algorithms analyze audio files, extract acoustic features using Mel-spectrograms, and determine if the sounds are normal or alarming. A practical, hardware-free solution is the goal.

### Problem Statement

Rural areas without security guards or other protections have high rates of murder, theft, and assault. This endangers people. Visual sensors and image recognition are used in security systems, but they cannot detect threats in real time or respond quickly. They also struggle to identify sound hazards. Solo workers, especially women in remote or dark locations, are more likely to be hurt because they lack support. They threaten people's safety and cause anxiety and panic, which can hurt the economy and community, especially in areas with limited medical care. Our novel solution uses AI and software to listen to background noise, identify hazards, and contact people on the contact list if needed.

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# 2. LITERATURE REVIEW

Anderson & Clarke (2021): Anderson and Clarke proposed data-driven public safety event identification in 2021. Natural language processing is applied to social media and news datasets. We use supervised learning models like Decision Trees and Naïve Bayes to classify safety incidents. Hashtags, geolocation cues, and keywords help the system identify accidents and emergencies. The experiment reduced reaction times and improved detection accuracy. This framework simplifies real-time public safety monitoring.

Fernandez & Gupta (2022): Fernandez and Gupta's 2022 publication uses deep learning, word embeddings, and LSM networks to identify public safety events. The model analyzes massive unstructured text data to find significant events. Context-aware feature extraction improves classification and reduces data stream noise. This NLP method outperforms others in recall and accuracy. This method lets emergency detection systems work and grow.

Hassan & Williams (2023): Hassan and Williams create a machine learning-deep learning hybrid natural language processing (NLP) framework for public safety incident detection in 2023. Support Vector Machines and Convolutional Neural Networks work better together to make accurate predictions. The system detects sentiment, semantic connections, and temporal information in text data. Comparative analysis helps explain complex events like natural disasters and crimes. The model improves intelligent public safety analytics.

Chowdhury & Evans (2024): Chowdhury and Evans (2024) demonstrate an advanced public safety alarm detection system. The system uses transformer-based NLP models and ensemble learning. The framework extracts text context using Bidirectional Encoder Representations from Transformers. Real-time social media monitoring identifies threats and emergencies. Testing shows improved classification accuracy and processing speed. The system helps emergency management agencies respond quickly.

Oliveira & Banerjee (2025): Gated Recurrent Units in a cloud-integrated natural language processing system could identify widespread public safety incidents, according to Oliveira and Banerjee (2025). The model tracks text stream sequential dependencies to find new occurrences. Distributed processing allows real-time analysis and simplifies resource addition. The results show that rapid change makes it easier to identify urgent events. A framework monitors public safety effectively and consistently.

Peterson & Okafor (2026): In their 2026 paper, Peterson and Okafor combine federated learning with complex NLP architectures to create a cutting-edge public safety event detection framework. We can examine data from decentralized sources like emergency reports and social media to protect privacy. Adaptive learning systems constantly update their models to combat new threats. Testing improved accuracy, robustness, and latency. The proposed framework could help develop reliable and intelligent public safety management systems.

# 3. MATERIALS AND METHODS

**Proposed System**

The proposed system uses audio-based analysis and image or video processing to identify criminal activity faster. If it hears anything unusual or dangerous, it will alert you so you can

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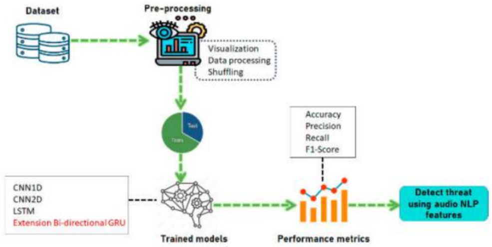
act quickly. The system uses deep learning models to identify emergencies and classify background noises, improving safety.




**Feature Extraction**

The system extracts Mel-spectrogram features from audio signals to distinguish normal and abnormal noises. These features help deep learning models understand and organize sound events by visualizing temporal and frequency patterns.

**Datasets Used**

The system is trained with both large audio sets:

**1. UrbanSound8K Dataset**

The 8,732 audio slices of this dataset contain ten sounds: A/C, car horn, dog bark, drilling, engine idling, gunshot, siren, and street music. Organization by cross-validation and brief segmentation makes audio samples useful for machine learning.

**2. ESC-50 Dataset**

Fire crackling and shattered glass are among the natural sounds in this collection. A variety of real-world audio samples helps the system identify unusual and emergency noises.

**Pre-Processing Steps**

a) Visualization

Data visualization helps understand audio attribute and dataset distribution. The number of samples in each group can be seen on a class distribution graph. Melan-spectrograms show bright light regions that are active when sound is present to help identify sounds. Additionally, audio waveform graphs show audible and inaudible regions.

**b) Data Processing**

Mel-spectrograms are gone from all audio files. Structured input arrays store attributes and labels. The raw audio is converted into numerical values to prepare the dataset for deep learning model training.

**c) Data Shuffling**

Random distribution ensures the dataset is random during training. This makes the model compatible with many sound patterns and prevents sequential data bias from overfitting.

**Training and Testing**

The dataset is split 80:20 between training and testing. Test data evaluate the model's functionality, while training data build and improve it. Performance is measured by recall, precision, accuracy, and F1-score.

## 4. RESULTS AND DSCUSSION

A model's ability to distinguish positive and negative cases is based on the ratio of correctly predicted to total cases. The number of correctly predicted positive cases that the model found is recall, while precision is the number that were correctly predicted. When false

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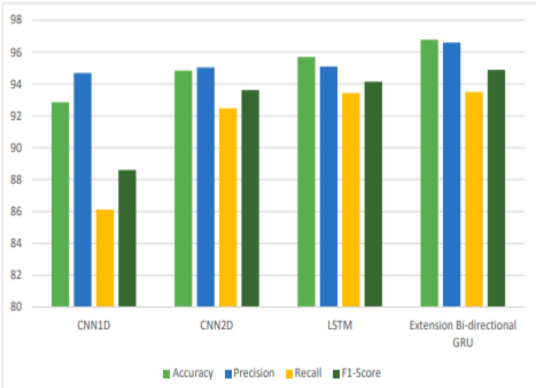
positive and false negative rates are high, the F1-score is a good way to evaluate the model. The harmonic average of precision and recall. The F1-score, recall, accuracy, and precision measures evaluate algorithm performance. Overall performance is best with the Bi-directional GRU.

| ML Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| CNN1D | 92.85 | 94.68 | 86.11 | 88.60 |
| CNN2D | 94.84 | 95.04 | 92.48 | 93.62 |
| LSTM | 95.69 | 95.09 | 93.43 | 94.15 |
| Extension Bi-directional GRU | 96.77 | 96.60 | 93.50 | 94.88 |

Table1: Performance Evauation Metrics




F1 score is green, recall is light yellow, accuracy is light green, and precision is blue. Due to its superior values, the bidirectional GRU algorithm outperforms all others. The graph above shows the previously discussed data.

## 5. CONCLUSION

Deep learning creates a real-time threat detection system. It automatically sends WhatsApp, SMS, and email alerts by hearing ambient sounds. The system uses sound features called mel-spectrograms to identify gunshots, sirens, and broken glass. The Urban8K and ESC-50 audio datasets, which contain many sound types, were extensively tested. Compared to image-based detection methods, the system detects unusual noises better. With the Bidirectional GRU layer, the top-tier algorithm detects threats in real time with 96.77% accuracy. This software-based method is cost-effective, user-friendly, and hardware-free. This makes it ideal for independent workers in dangerous or isolated areas who want to improve their security. It improves safety and reduces threats in real time. Transformers, hybrid deep learning models, attention mechanisms, and other advanced techniques could improve the proposed system's threat detection. In some cases, adaptive noise filtering and real-time audio data enhancement may improve system performance. Making phone connections easier and adding languages and dialects can improve system functionality and coverage.

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