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Live Event Detection for People's Safety Using NLP and Deep Learning

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ABSTRACT

This project presents a real-time abnormal sound detection system for public safety using a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architecture. The system continuously listens to environmental sounds and identifies potentially dangerous events such as screams, explosions, gunshots, or violent disturbances. Unlike traditional single-stage models, the proposed CNN-LSTM approach combines the spatial feature extraction capability of CNNs with the temporal sequence learning strength of LSTMs, enabling effective recognition of complex and noisy sound patterns. Captured audio signals are converted into mel-spectrograms and fed into the CNN-LSTM model to extract deep acoustic features for highly accurate abnormal-event classification. When a threat is detected, the system instantly alerts users, ensuring quick response during critical situations. This method reduces false alarms, enhances robustness in real-world noisy environments, and achieves strong performance without requiring extremely large manually labeled datasets.

Keywords: Abnormal Sound Detection, CNN-LSTM Model, Real-Time Alert System, Emergency Response, Acoustic Event Classification.

I. INTRODUCTION

Sound plays a crucial role in identifying dangerous or emergency situations in everyday environments. Events such as explosions, screams, or gunshots often occur unexpectedly and can indicate immediate threats to personal or public safety. Traditional surveillance systems rely mainly on visual monitoring or manual reporting, which may fail during critical moments. Hence, intelligent acoustic event detection has become an essential component of modern safety systems.
Deep learning has significantly improved the capability of machines to understand complex audio patterns. Among several architectures, CNN-LSTM models have shown excellent performance due to their ability to capture both frequency-based spatial features and time-based sequential patterns in sound. CNN layers process the spectral representation of audio, while LSTMs understand the evolution of sound over time, making this approach ideal for real-world acoustic analysis.

This project utilizes a CNN-LSTM model to build a real-time abnormal sound detection system capable of identifying threatening sounds and categorizing them based on their severity. Audio signals are converted into mel-spectrograms and passed through the hybrid neural network for classification. The system reliably distinguishes between normal and abnormal sounds, even in noisy and unpredictable environments.

To make the system practical and user-friendly, the project is divided into two modules: **Admin** and **User**. The admin module allows dataset management, preprocessing, and model training, ensuring that the classifier remains updated and accurate. The user module provides features such as profile setup, guardian registration, real-time prediction, SOS alerts, and automated notification with GPS location when a high-level threat is detected.

By integrating deep learning, real-time prediction, and emergency communication mechanisms, this system offers a comprehensive solution for safety enhancement. It provides immediate alerting through email notifications and accurate location tracking, making it valuable for personal safety apps, smart city surveillance, women's safety solutions, and automated monitoring systems. Overall, the project demonstrates how intelligent sound analysis can significantly contribute to faster emergency response and improved situational awareness.

II. LITERATURE SURVEY

1. Title: Live Event Detection for People's Safety Using NLP and Deep Learning

Authors: C. Rashmi, B. Soumya, A. Harika, D. Harathi

Abstract:
This study proposes a real-time event detection system using audio signals and machine learning techniques to enhance public safety. The system extracts audio features such as MFCC, spectral contrast, and chroma features, and applies the LightGBM classifier for event classification. It detects abnormal sounds like explosions, screams, and disturbances in live environments. The model demonstrates high accuracy, low latency, and scalability, making it suitable for real-time deployment. The research highlights how intelligent audio analysis can improve situational awareness and assist authorities in preventing potential threats.

2. Title: Real-Time Event Detection for Public Safety Using Bi-LSTM and NLP

Authors: Balusamy D., Geetha S., Srihari S.

Abstract:
This paper introduces a deep learning-based approach using Bidirectional LSTM, CNN, and NLP techniques to detect dangerous events from environmental sounds. The system analyzes audio signals such as gunshots, screams, and glass breaking to identify threats. It aims to reduce false alarms and improve detection accuracy. Alerts are sent via SMS or email for quick response. The proposed system enhances real-time monitoring and ensures better safety in public environments.

3. Title: A Novel Multi-Modal Deep Learning Approach for Real-Time Live Event Detection Using Audio and Video

Authors: Pavadareni R., A. Prasina, et al.

Abstract:
This research presents a multi-modal framework combining audio and video data for improved event detection. The system uses CNN and LSTM models to process temporal and spatial features from both modalities. Audio features (MFCC) and visual features (ResNet) are fused to enhance detection accuracy. The approach overcomes limitations of single-modal systems and improves robustness in dynamic real-world environments, making it suitable for safety-critical applications.

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4. Title: Real-Time Event Detection Using Recurrent Neural Networks in Social Sensors

Authors: Van Quan Nguyen, Tien Nguyen Anh, Hyung-Jeong Yang

Abstract:
This study focuses on event detection using textual data from social media platforms. It combines CNN and RNN models with word embeddings to extract meaningful patterns from large-scale text data. The system captures temporal features using LSTM networks to detect real-time events. It demonstrates strong performance even with imbalanced datasets and highlights the importance of NLP-based event detection in monitoring real-world incidents.

5. Title: Event Recognition Based on Deep Learning in Text Data

Authors: Yajun Zhang, Zongtian Liu, Wen Zhou

Abstract:
This paper explores event detection in textual data using deep learning techniques. It focuses on identifying trigger words that indicate specific events in natural language. The system uses neural networks to improve accuracy in recognizing event patterns from large datasets. The research forms a foundation for NLP-based event detection systems and contributes to advancements in automated text understanding for safety applications.

III. EXISTING SYSTEM

The existing system for detecting dangerous or abnormal situations primarily relies on capturing environmental audio using a smartphone's built-in microphone. The system continuously monitors surrounding sounds and records audio signals in real time. These audio signals are then preprocessed and converted into visual representations known as spectrograms, which help in analyzing the frequency and intensity patterns of the sound over time.

Deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are applied to these spectrograms to classify and recognize different types of sounds. CNN models are effective in extracting spatial features from the spectrogram images, while LSTM models are useful for capturing temporal dependencies in sequential audio data. By combining these models, the system can accurately identify critical sounds such as screaming, gunshots, explosions, glass breaking, or other distress signals.

Once a suspicious or dangerous sound is detected, the system automatically generates alerts and sends notifications to concerned authorities or emergency contacts. This enables quick response during emergencies and helps improve public safety. However, the system mainly focuses on audio data and may face challenges in noisy environments or when multiple sound sources overlap.

IV. PROPOSED SYSTEM

The proposed system aims to enhance real-time detection of dangerous or abnormal sounds by leveraging a hybrid deep learning approach that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. While maintaining the core objective of identifying critical events and sending immediate alerts, this system improves accuracy, reliability, and responsiveness compared to traditional models.

In this approach, environmental audio is continuously captured through a microphone and preprocessed into mel-spectrograms, which provide a detailed representation of sound frequency and intensity over time. The

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CNN component is responsible for extracting spatial features from these spectrograms, such as patterns, frequency variations, and intensity differences. These features help in identifying distinct characteristics of different sounds.

Subsequently, the LSTM component processes the extracted features to analyze temporal dependencies, enabling the system to understand how sound patterns evolve over time. This combination allows the model to accurately classify complex audio events such as gunshots, screams, explosions, and other abnormal sounds.

Once a potential threat is detected, the system instantly generates alerts and notifies the user or relevant authorities. This rapid response mechanism ensures timely intervention during emergencies, thereby improving overall public safety and situational awareness.

V. SYSTEM ARCHITECTURE

The system architecture for live event detection is designed to process real-time environmental data and identify potentially dangerous situations using deep learning techniques. It consists of several interconnected components, including the **Audio Input Module**, **Preprocessing Unit**, **Feature Extraction Layer**, **Deep Learning Model (CNN-LSTM)**, and **Alert System**, all working together to ensure accurate and timely event detection.

The process begins with the **Audio Input Module**, where environmental sounds are continuously captured using a microphone or sensor device. This raw audio data is passed to the **Preprocessing Unit**, which cleans the data by removing noise and converting it into a suitable format. The audio signals are then transformed into **mel-spectrograms**, which visually represent sound frequencies over time.

Next, the **Feature Extraction Layer** uses Convolutional Neural Networks (CNN) to extract spatial features such as frequency patterns, intensity variations, and unique sound characteristics from the spectrograms. These extracted features are then fed into the **LSTM (Long Short-Term Memory) layer**, which analyzes temporal dependencies and sequential patterns in the audio data. This helps the system understand how sounds evolve over time, improving detection accuracy.

The **Classification Module** determines whether the detected sound corresponds to a normal or abnormal event, such as a scream, gunshot, or explosion. If a threat is identified, the **Alert System** is triggered, which sends real-time notifications to users or authorities via mobile alerts, SMS, or email.

Overall, the architecture ensures **real-time processing, high accuracy, and quick response**, making it highly effective for enhancing public safety and emergency response systems.

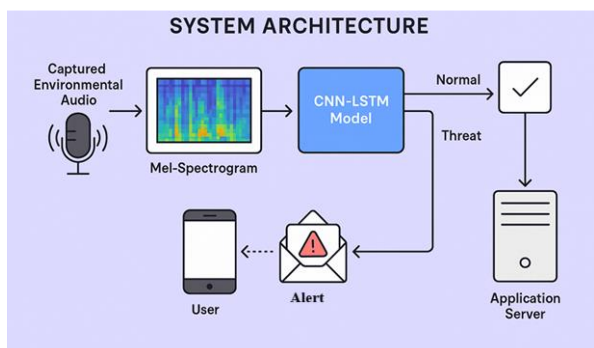

Fig 5.1: System Architecture

VI. IMPLEMENTATION

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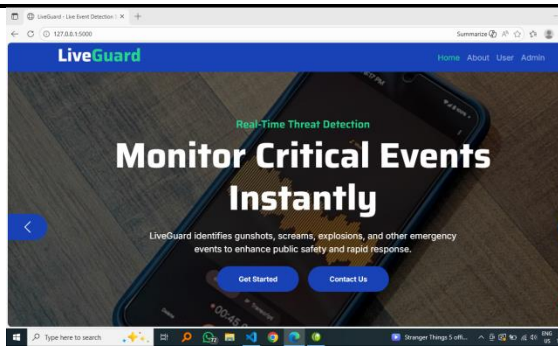

Fig 6.1: Dash board

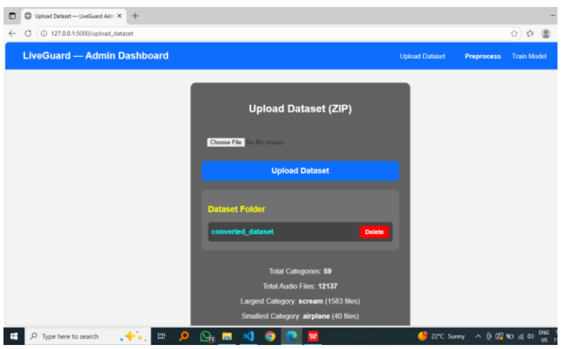

Fig 6.2: Dataset page

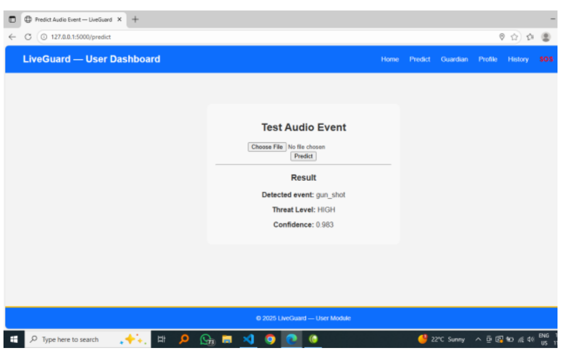

Fig 6.3: Test Audio Page

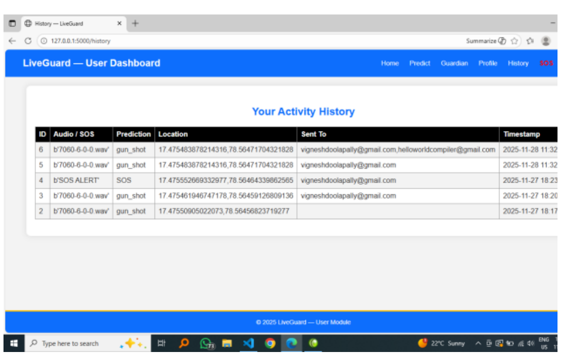

Fig 6.4: User Activity Page

VII. CONCLUSION

The proposed real-time abnormal sound detection system using a CNN-LSTM architecture effectively enhances safety monitoring by accurately identifying critical sounds in real-world environments. The hybrid model efficiently distinguishes between normal and dangerous sounds, enabling quick detection of events such as screams, explosions, and gunshots. By combining CNN-based spatial feature extraction with LSTM-based temporal analysis, the system achieves high accuracy, strong robustness against background noise, and reliable performance in dynamic conditions. The automated alert mechanism ensures that emergency contacts receive immediate notifications, supporting rapid assistance during critical situations. Overall, this project demonstrates that integrating CNN-LSTM with real-time audio processing provides a dependable, scalable, and efficient solution for improving personal and public safety through intelligent acoustic event detection.

VIII. FUTURE SCOPE

The proposed system can be further enhanced by integrating advanced technologies to improve accuracy, scalability, and real-world applicability. One significant improvement is the incorporation of **multi-modal data**, combining audio with video surveillance systems to provide more comprehensive event detection and reduce false positives. The integration of **Natural Language Processing (NLP)** can also enable the system to analyze emergency-related text data from social media or messages, enhancing situational awareness.

Additionally, deploying the system on **edge devices** and IoT platforms can enable faster processing with reduced latency, making it suitable for smart cities and real-time surveillance environments. The use of **federated learning** can improve privacy by allowing decentralized model training without sharing raw data.

Future work may also focus on improving robustness by using advanced deep learning models such as Transformers or attention-based architectures for better context understanding. Expanding the system to support **multiple languages and diverse sound environments** will increase its usability globally. Furthermore, integrating **real-time location tracking and automated emergency response systems** can significantly enhance public safety by enabling faster and more efficient incident handling.

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