

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

Dr. K. Praveen kumar¹, Mr. A. Sai Sudheer², Mr. Y. Sri Manikanta³, Mr. Y. Surya Prakash⁴

¹Associate Professor, Department of ECE, CMR Institute of Technology, Medchal, Hyderabad.

^{2,3,4}Bachelor's Student, Department of ECE, CMR Institute of Technology, Medchal, Hyderabad.

ABSTRACT:

Today, humans pose the greatest threat to society by getting involved in robbery, assault, or homicide activities. Such circumstances threaten the people working alone at night in remote areas especially women. Any such kind of threat in real time is always associated with a sound/noise which may be used for an early detection. Numerous existing measures are available but none of them sounds efficient due to lack of accuracy, delays in exact prediction of threat. Hence a novel software-based prototype is developed to detect threats from a person's surrounding sound/noise and automatically alert the registered contacts of victims by sending email, SMS, WhatsApp messages through their smartphones without any other hardware components. Audio signals from Kaggle dataset are visualized, analyzed using Exploratory Data Analytics (EDA) techniques. By feeding EDA outcomes into various Deep Learning models: Long short-term memory (LSTM), Convolutional Neural Networks (CNN) yields accuracy of 96.6% in classifying the audio-events.

Natural language processing (NLP), deep

learning, audio, recording, CNN, LSTM, classification, prediction.

INTRODUCTION:

In the physical world, the occurrence of any physical event would bear with it a sound, particular to that event only. Be it the sound of a stone falling to the ground, a river flowing, a bird chirping, a person walking, a road being constructed etc. It is thus fair to take into account, just like an event with which positivity can be associated (crowds cheering, friends greeting each other, celebratory fireworks etc.) has a sound paired with it, negative events (a road accident, a landslide, a gunshot etc.) also have specific sounds associated with them as well. It is worth pondering how great would be a system which would be able to detect ambient noise and judge whether it is related to something positive or something negative. Even if direct applications as described here are not available to mankind's everyday use, the technology which is required to make it a reality already exists in one form or the other. Before directly discussing the prospects of natural language processing in the domain of security, one needs to understand the current

scenario, and where and how sound/text detection/analysis is done by NLP and used by mankind in modern times. Modern smartphones equipped with Artificial Intelligence based voice recognition systems are classic examples of the application of speech-based natural language processing in our day-to-day lives. With the likes of Google's Voice Assistant [23], [24] available on every android powered smartphone which searches the web and brings the necessary information in front of us without us typing a single search keyword, or the evolution of Apple's Siri [24] through the various versions of the iconic iPhone series which primarily works as a personal assistant for its users, or the availability of Amazon's Alexa [26] as a smart home voice assistant which can be used to control virtually any smart electrical device in our home, or the development of Samsung's own artificial intelligence-based personal assistant named Bixby [25], natural language processing has already come a long way in the domain of voice/text-based language processing for the betterment of human lives, all while keeping at par with the compatibility with the latest technologies and hardware.

LITERATURE REVIEW:

1. Sound Analysis in Smart Cities

Authors: J.P. Bello et al. (2018)

J.P. Bello et al.[1] examined sound analysis in smart cities, presenting their findings in the book Computational Analysis of Sound Scenes and Events. Published in 2018, their

research explored various techniques for analyzing live event soundscapes, demonstrating the potential for improving city planning and noise management.

2. An Interpretable Deep Learning Model for Automatic Sound Classification

Authors: P. Zinemanas et al. (2021)

P. Zinemanas et al [2] developed an interpretable deep learning model for automatic sound classification. Their 2021 study in Electronics introduced a model capable of accurately classifying different sound types while providing interpretable results. The model employed a combination of convolutional neural networks (CNNs) and attention mechanisms to achieve high classification accuracy.

3. Environmental sound classification using convolution neural networks with different integrated loss functions

Authors: J.K. Das et al. (2023)

J.K. Das et al.[3] investigated environmental sound classification using convolutional neural networks with different integrated loss functions. Published in Expert Systems in 2021, their study demonstrated the effectiveness of CNNs in classifying a variety of environmental sounds. They experimented with various loss functions, such as cross-entropy and focal loss, to enhance model performance.

4. Live event sound Classification Using Convolutional Neural Network and Long Short Term Memory Based on Multiple Features

Authors: .K. Das, A. Ghosh, A.K. Pal, S. Dutta (2020)

J.K. Das et al.[4] presented a method combining convolutional neural networks and long short-term memory networks for live event sound classification. Their study, presented at the 2020 ICDS conference, showed that the hybrid model improved classification accuracy by leveraging both spatial and temporal features.

5. Efficient Classification of Environmental Sounds through Multiple Features Aggregation and Data Enhancement Techniques for Spectrogram Images

Authors: Z. Mushtaq and S.F. Su (2020)

Z. Mushtaq and S.F. Su [5] explored efficient classification of environmental sounds through multiple features aggregation and data enhancement techniques. Published in Symmetry in 2020, their study focused on enhancing spectrogram images to improve classification accuracy. They aggregated features from different spectrogram representations and applied data augmentation techniques to create a more robust training dataset.

EXISTING SYSTEM:

Live event sound classification and analysis play a critical role in monitoring and managing noise pollution in city environments. Effective noise management requires accurate identification and classification of various live event sounds, such as traffic noise, construction sounds, and human activities. Traditionally, the

classification of live event sounds has relied on manual methods, which involve the collection and analysis of sound recordings by human experts.

DISADVANTAGES OF EXISTING SYSTEM:

- 1) Time-Consuming
- 2) Inconsistency

PROPOSED SYSTEM:

This research project focuses on classifying live event sounds by first collecting a diverse dataset of audio files categorized by sound types like traffic, sirens, and human chatter. The audio data undergo preprocessing to remove noise and extract meaningful features using Mel-frequency cepstral coefficients (MFCCs). Categorical sound labels are then encoded numerically, and the dataset is split into training and testing sets to evaluate model performance reliably. Two machine learning algorithms are compared: the existing Multi-Layer Perceptron (MLP) and the proposed LightGBM (LGBM), with LGBM offering faster training and better handling of large datasets. The final model predicts sound categories from new audio samples, demonstrating its effectiveness in real-world applications.

ADVANTAGES OF PROPOSED SYSTEM:

- 1) High accuracy
- 2) High efficiency

BLOCK DIAGRAM:

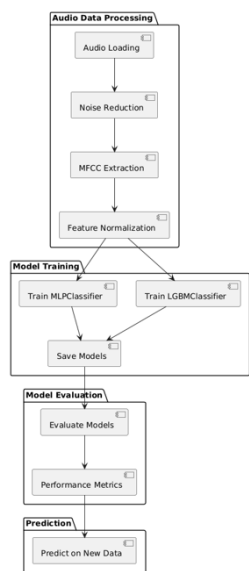


Figure1: Block diagram of the system

RESULT:

To visualize the distribution of different sound categories in the dataset, a bar plot was created using the counts of each category. The count of sounds per category was calculated by iterating through the directory structure where the audio files are stored, and the results were compiled into a pandas DataFrame. The bar plot, with categories on the x-axis and their respective counts on the y-axis, displayed in a sky-blue colour scheme, provides a clear overview of the number of audio samples available for each sound category. The plot includes labels for

both axes, a title, and rotated category labels for better readability, ensuring a well-organized and informative visualization.

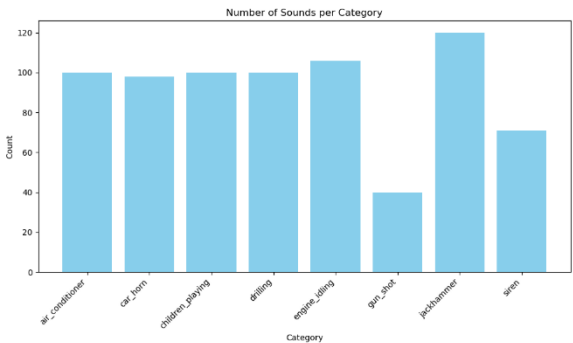


Figure 2: Count Plot for sound categories

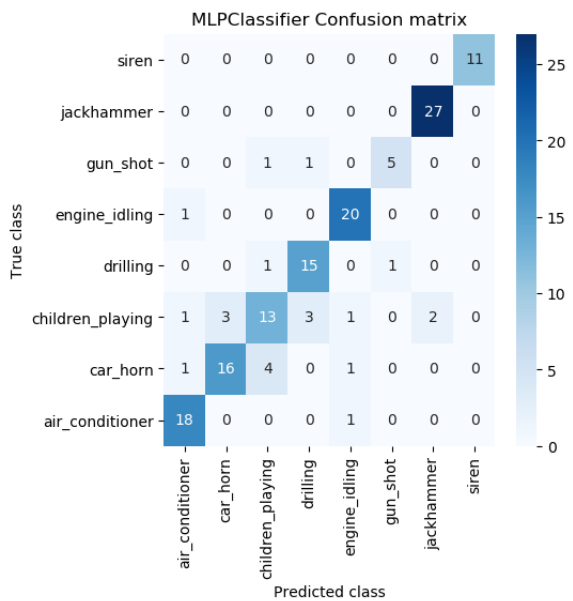


Figure 3: Multi-Layer Perceptron (MLP) model

CONCLUSION:

This project on live event sound classification utilizing a comprehensive dataset has successfully demonstrated the effectiveness of machine learning models, particularly the LightGBM classifier, in

accurately identifying various live event sounds. The dataset was meticulously curated and preprocessed, ensuring high-quality audio input for feature extraction. By comparing the performance of the LightGBM and the existing Multi-Layer Perceptron (MLP) classifier, the results indicated a marked improvement in classification accuracy, precision, recall, and F1-score with the proposed algorithm. This highlights the potential of advanced machine learning techniques in tackling real-world challenges in live event sound analysis, contributing to enhanced urban planning, noise monitoring, and public safety initiatives.

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