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Siren Detection and Localisation in Autonomous Vehicles

A Minor Project Report (18EC64)

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Bachelor of Engineering in

Electronics and Communication Engineering

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RV College of Engineering®, Bengaluru

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Department of Electronics and Communication Engineering

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CERTIFICATE

Certified that the major project (18EC81)work titled ***Siren Detection and Localisation in Autonomous Vehicles*** is carried out by **Mukkamala Ananya** (**1RV20EC104**), **Nisarg Pyage** (**1RV20EC109**), **Rachana M** (**1RV20EC119**) and **Shashwat Lavaniya** (**1RV20EC144**) who are bonafide students of RV College of Engineering, Bengaluru, in partial fulfillment of the requirements for the degree of **Bachelor of Engineering** in **Electronics and Communication Engineering** of the Visvesvaraya Technological University, Belagavi during the year 2022-23. It is certified that all corrections/suggestions indicated for the Internal Assessment have been incorporated in the major project report deposited in the departmental library. The major project report has been approved as it satisfies the academic requirements in respect of major project work prescribed by the institution for the said degree.

Signature of Guide	Signature of Head of the Department	Signature of Principal
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Name of Examiners	Signature with Date
1.	
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DECLARATION

We, **Mukkamala Ananya** , **Nisarg Pyage** , **Rachana M** and **Shashwat Lavaniya** students of sixth semester B.E., Department of Electronics and Communication Engineering, RV College of Engineering, Bengaluru, hereby declare that the major project titled '**Siren Detection and Localisation in Autonomous Vehicles**' has been carried out by us and submitted in partial fulfilment for the award of degree of **Bachelor of Engineering** in **Electronics and Communication Engineering** during the year 2022-23.

Further we declare that the content of the dissertation has not been submitted previously by anybody for the award of any degree or diploma to any other university.

We also declare that any Intellectual Property Rights generated out of this project carried out at RVCE will be the property of RV College of Engineering, Bengaluru and we will be one of the authors of the same.

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ABSTRACT

Autonomous vehicles have become a convenient and advanced means of transportation, and the features that are being used with the help of Artificial Intelligence have changed the world. However, the increased number of vehicles on the road can sometimes create problems for the movement of emergency vehicles, especially in cities. To address this issue, the idea of siren detection and localization has emerged. Through Machine Learning and Deep Learning, the sound and location of emergency vehicles can be detected, even if they are far away from the autonomous vehicle, so that the driver can make a path for the emergency vehicle.

This work discusses the importance of developing algorithms for detecting and localizing emergency sirens in autonomous vehicles to enhance safety. The dynamic nature of the urban environment and diverse acoustic conditions make it challenging to detect and accurately localize emergency sirens. The work aims to develop an LSTM-based algorithm for the detection and building a theoretical model for precise localization of emergency sirens. The work utilizes acoustic sensors and a simulated model in MATLAB to demonstrate the potential to equip autonomous vehicles with the capability to identify and locate emergency sirens accurately in complex urban environments. The time gap between the transmitted and received audio signal is observed and also the theoretical distance is calculated .The siren detection and localization system achieved an average classification rate of 94 percent. The work highlights the potential of this advancement for safer navigation and efficient decision-making in response to emergency vehicles auditory signals.The software employed for system involves several tools and libraries that work together to detect and locate the source of a siren sound. These tools and libraries provide enhanced capabilities for programming, machine learning, deep learning, signal processing, and data analysis, making it possible to build accurate and efficient siren detection and localization systems.

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Chapter 1

INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1 SIREN DETECTION AND LOCALISATION IN AUTONOMOUS VEHICLES

As the world of autonomous vehicles continues to evolve, ensuring the safety of both passengers and pedestrians becomes paramount. One crucial aspect of this safety is the ability of autonomous vehicles to detect and localize emergency sirens, such as those from ambulances, police cars, and fire trucks. These sirens serve as critical auditory signals that can indicate the presence of an emergency vehicle and the urgency of its movement. Detecting and accurately localizing such sirens is a challenging task due to the dynamic nature of the urban environment and the diverse acoustic conditions.The figure should be referenced in the text as Figure. 1.1

This project aims to enhance the safety of autonomous vehicles by developing an LSTM-based algorithm for the detection and building a theoretical model for precise localization of emergency sirens. By utilizing acoustic sensors and a simulated model in MATLAB, the project demonstrates the potential to equip autonomous vehicles with the capability to identify and locate emergency sirens accurately in complex urban environments. This advancement holds promise for safer navigation and efficient decision-making in response to emergency vehicles' auditory signals.

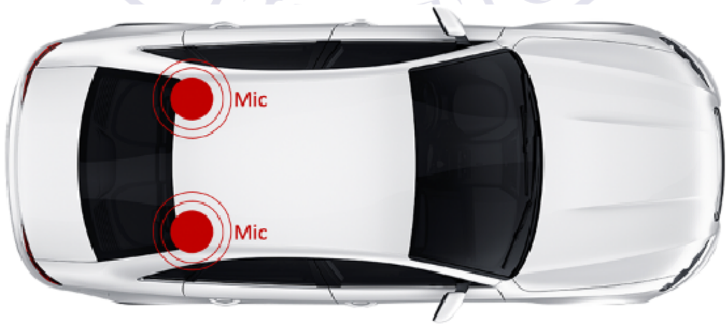

Figure 1.1: Autonomous vehicle

These guidelines are provided to formally expose the various ethical and technical issues involved in writing up the work and the format that are required to adhere to while submitting the project report.

1.2 Motivation

In the realm of autonomous vehicles, prioritizing safety is paramount. Detecting and localizing emergency sirens, vital indicators of urgent situations, presents challenges due to urban dynamics and acoustic complexities. To address this, leveraging deep learning's Long Short-Term Memory (LSTM) networks stands out. This project centers on an LSTM-based algorithm that processes audio input from vehicle-installed sensors, distinguishing emergency sirens from urban noise. This empowers autonomous vehicles to promptly recognize and respond to siren signals accurately. In urban environments, precise siren localization aids safe navigation. MATLAB simulations, employing Time Difference of Arrival (TDOA) algorithms, enable theoretical model training for real-world applications. This innovation equips autonomous vehicles with a crucial safety tool for efficient decision-making, safeguarding passengers and pedestrians.

1.3 Problem statement

To develop a precise and real-time siren detection and localization system for autonomous vehicles, effectively distinguishing emergency vehicle sirens from ambient noise and accurately estimating their direction and distance.

1.4 Objectives

The objectives of the project are:

1. To develop a siren detection algorithm that can reliably and accurately identify siren sounds within noisy and dynamic urban environments.

2. To develop a real-time localization system that can quickly determine the precise geographic location of the siren source, allowing emergency services to respond promptly and navigate effectively.

1.5 Literature Review

Listening for Sirens: Locating and Classifying Acoustic Alarms in City Scenes" is a research paper that proposes a novel approach to detect and classify acoustic alarms in urban environments using deep learning techniques. The paper aims to detect and localize horns and sirens of emergency vehicles in urban environments, which can be challenging due to the copious, unstructured, and unpredictable traffic noise.

The paper proposes a system that combines semantic segmentation and sound source localization to detect and classify acoustic alarms in urban scenarios. The paper focuses on detecting and localizing horns and sirens of emergency vehicles in urban environments, which can be challenging due to the copious, unstructured, and unpredictable traffic noise. The proposed system uses deep learning techniques to analyze the audio data and accurately identify the location of the siren. The paper provides a detailed description of the system architecture, the dataset used for training and testing, and the evaluation results. The proposed system achieves high accuracy in detecting and localizing sirens in various driving scenarios, including urban and rural environments. The paper also discusses the limitations and future research directions for this technology.[1]

The paper presents a real-time siren detector that is designed to improve the safety of guides in traffic environments. The siren detector is tested on real signals acquired and recorded in city streets with various traffic and sound sources. The paper discusses the development of a small, inexpensive Atmel microcontroller-based siren detection system that is capable of discriminating the siren signal from other sounds in the environment. The system uses a pitch detection algorithm that is capable of extracting the periodic (siren) signal from aperiodic (speech, automobile horn) ones. The algorithm is able to detect the emergency vehicle in the presence of pitched and non-pitched noise, and it outperforms complex pattern recognition algorithms. The siren signal miss rate of the algorithm is very low.[2]

The paper presents a large-scale audio dataset for emergency vehicle sirens and road noises. The dataset includes over 10,000 audio clips of emergency vehicle sirens and road noises collected from various locations and environments. The dataset is intended for training and evaluating machine learning models for siren detection and classification. The paper highlights the importance of such datasets in controlling traffic flow, reducing traffic congestion, and improving emergency response time, especially for fire and health-related incidents. The dataset is divided into two labeled classes, one for emergency vehicle sirens and one for traffic noises. The paper describes the collection and pre-processing of audio data using different methods to develop a high-quality and clean dataset. The developed dataset offers a high quality and range of real-world traffic sounds and emergency vehicle sirens. The paper provides valuable insights into the development of large-scale audio datasets for siren detection and classification, which can be useful in various applications, including autonomous driving and traffic safety systems.[3]

The paper proposes a new regional localization method for indoor sound sources using convolutional neural networks (CNNs). The method involves extracting features from sound signals using CNNs and applying a regression algorithm to estimate the source location. The effectiveness of the proposed method is demonstrated through experiments with both simulated and real sound signals.The research method focuses on developing a system that can accurately locate indoor sound sources. By utilizing CNNs, the method takes advantage of the network's ability to learn spatial features from the sound signals. The extracted features are then used in a regression algorithm to estimate the location of the sound source within the indoor environment. The paper likely discusses the process of data collection, including the creation of simulated room databases and the collection of real room databases. It also describes the data processing techniques used to prepare the sound signals for analysis. The proposed CNN-R architecture, which combines CNNs with regression models, is likely explained in detail.The experimental results presented in the paper demonstrate the performance of the proposed method. Metrics such as high precision and high accuracy are likely used to evaluate the localization accuracy.[4]

The paper focuses on the task of locating and classifying acoustic alarms, specifically emergency vehicle sirens, in city scenes. The paper likely discusses various techniques and approaches for detecting and classifying these acoustic alarms in urban environments. The research aims to address the challenge of detecting and localizing the presence of sirens and other alerting urban sounds in complex acoustic scenes. The paper may explore methods such as adaptive filtering techniques, peak searching, and spectral analysis to detect and differentiate the target signals from background noise. The proposed framework may involve a two-stage approach, where the urban acoustic events are first modeled, followed by the detection and classification of specific alarms like sirens and horns. The paper likely presents experimental results and evaluations to demonstrate the effectiveness of the proposed methods in detecting and localizing emergency vehicle sirens in city environments.[5]

The paper presents a real-time acoustic perception system for automotive applications. The system utilizes microphones and sensors to detect and classify various acoustic events, including sirens, horns, and engine sounds. The effectiveness of the system is demonstrated through experiments in real-world driving scenarios. The paper highlights the importance of acoustic perception in autonomous driving and traffic safety systems, where the ability to detect and classify various acoustic events can improve the safety of drivers and passengers. The paper may explore various deep learning-based methods for acoustic event detection, such as neural network-based deep learning and time-delay neural networks. The proposed system may involve a combination of hardware and algorithm co-design to enable real-time operation and accurate detection and classification of acoustic events.[6]

The paper focuses on acoustic event detection and classification in urban environments using deep learning techniques. The paper likely discusses the application of deep learning models, such as convolutional neural networks (CNNs), for detecting and classifying various acoustic events, including emergency vehicle sirens. The effectiveness of deep learning-based approaches in urban sound environments and their potential applications in areas such as traffic monitoring and public safety may be explored. The paper may present experimental results and evaluations to demonstrate the performance of the proposed deep learning models in detecting and classifying acoustic events in urban environments.[7]

The paper discusses the use of convolutional neural networks (CNNs) with temporal activation functions for acoustic event detection. The paper may explore how temporal information can be incorporated into CNN architectures to improve the accuracy of event detection. The proposed approach may involve the extraction of temporal features from sound signals using CNNs and the application of temporal activation functions to improve the classification accuracy. The paper may present experimental results and evaluations to demonstrate the effectiveness of the proposed approach in detecting and classifying acoustic events, including sirens. The paper may also discuss the potential applications of the proposed approach in areas such as traffic monitoring and public safety. The use of deep learning techniques for acoustic event detection and classification is an active area of research, and the paper provides valuable insights into the development of deep learning-based approaches for acoustic event detection.[8]

The paper focuses on the detection and localization of acoustic events, including emergency vehicle sirens, using a microphone array on a moving robot. The paper may discuss the use of microphone arrays and localization algorithms to estimate the source location of acoustic events. The proposed method may involve the use of a two-stage approach, where the urban acoustic events are first modeled, followed by the detection and localization of specific alarms like sirens and horns. The paper may present experimental results and evaluations to demonstrate the effectiveness of the proposed method in detecting and localizing sirens in real-world scenarios. The paper may also discuss the potential applications of the proposed approach in areas such as traffic monitoring and public safety. The use of microphone arrays and localization algorithms for acoustic event detection and localization is an active area of research, and the paper provides valuable insights into the development of such methods for urban sound environments.[9]

The paper presents a real-time siren detector designed to improve the safety of guides in traffic environments. The paper discusses the development of a small, inexpensive Atmel microcontroller-based siren detection system that is capable of discriminating the siren sound from other sounds in the environment. The paper may describe the testing and evaluation of the system on real signals acquired in city streets with various traffic and sound sources. The effectiveness of the proposed siren detection system in improving traffic safety may be demonstrated through experimental results and evaluations. The paper may also discuss the potential applications of the proposed approach in areas such as traffic monitoring and public safety. The development of real-time siren detection systems is an active area of research, and the paper provides valuable insights into the development of such systems for traffic safety.[10]

1.6 Brief Methodology of the project

Beginning with audio signal capture through acoustic sensors, the process involves converting signals into .wav files for a dataset of 2800 samples. Feature extraction reveals tonal content, spectral details, and more. Labels are associated for supervised learning. Data is structured into a CSV file, compatible with machine learning algorithms. The LSTM architecture then learns from the CSV dataset, capturing temporal dependencies. Testing evaluates the model's accuracy with new audio samples. These steps collectively create an efficient emergency sound detection system, vital for enhancing autonomous vehicle safety.

The sounds are recorded and to verify the accuracy the audio files are converted to .wav files and using MATLAB the waveforms are generated where the time gap is obtained. MATLAB codes are used to obtain the coordinates of the receiver which is calculated using Euclidean distance formula. These steps collectively help us in verifying the practical data with the theoretical data.

1.7 Organization of the report

This report is organized as follows. Write the discussions in each chapter. A sample is as follows.

- Chapter 2 discusses about siren detection and localisation.
- Chapter 3 discusses about the software and hardware utilization.
- Chapter 4 discusses about the methodology used in detection and localisation.
- Chapter 5 discusses about simulation results and discussions.
- Chapter 6 discusses about conclusions and future scope.

The report ends with code and bibliography.

Chapter 2

SIREN DETECTION AND LOCALIZATION

CHAPTER 2

SIREN DETECTION AND LOCALIZATION

As the world of autonomous vehicles continues to evolve, ensuring the safety of both passengers and pedestrians becomes paramount. One crucial aspect of this safety is the ability of autonomous vehicles to detect and localize emergency sirens, such as those from ambulances, police cars, and fire trucks. These sirens serve as critical auditory signals that can indicate the presence of an emergency vehicle and the urgency of its movement. Detecting and accurately localizing such sirens is a challenging task due to the dynamic nature of the urban environment and the diverse acoustic conditions.

One approach to effectively tackle this challenge is by harnessing the capabilities of advanced deep learning techniques, with a specific focus on Long Short-Term Memory (LSTM) networks. LSTMs represent a subset of recurrent neural networks (RNNs) and stand out for their exceptional proficiency in capturing intricate temporal relationships inherent in sequential data. This remarkable attribute renders LSTMs ideally suited for handling complex tasks that hinge on the intrinsic time-series attributes, such as the intricate patterns present in audio signals. By leveraging the inherent memory and sequence modeling of LSTMs, the endeavor to detect and localize emergency sirens within the ever-evolving landscape of autonomous vehicles gains a robust framework capable of addressing the dynamic and nuanced challenges posed by urban soundscapes.

In this project, the main focus is on the development of an LSTM-based algorithm for the detection and localization of emergency sirens in autonomous vehicles. The algorithm is designed to process audio input from acoustic sensors installed within the vehicle, enabling it to differentiate between typical urban noise and the distinct sound patterns of emergency sirens. The primary goal is to equip the autonomous vehicle with the ability to recognize these specific siren signals promptly and accurately.

2.1 Detection Methodology

The detection process begins by capturing audio signals through acoustic sensors, a foundational step crucial for identifying various sound sources. These signals are then converted into .wav files, a common digital audio format that preserves the integrity of the captured audio. Notably, the dataset comprises a substantial collection of 2800 samples, which were obtained from Kaggle a reputable platform known for its diverse and extensive datasets. Leveraging these curated samples adds a valuable real-world aspect to theoretical model.The figure should be referenced in the text as Figure. 2.1

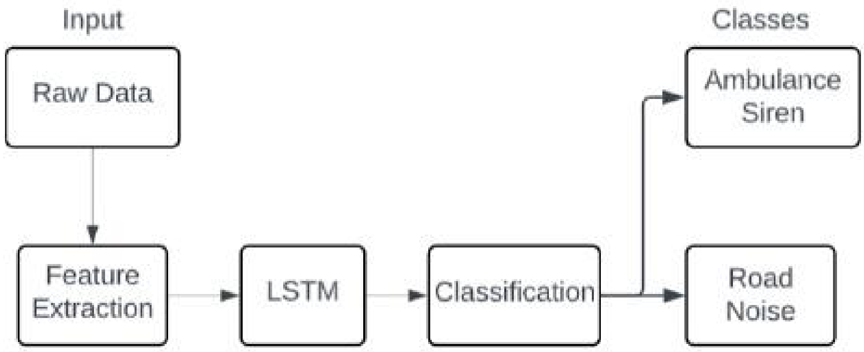

Figure 2.1: Detection Methodology

Upon acquiring the dataset, a pivotal stage follows, involving feature extraction. This step extracts pertinent characteristics from the audio data that encapsulate meaningful information about each sound class. Among these features, the chromastft quantifies tonal content, offering insights into the pitch and harmonic relationships. Meanwhile, the spectralcentroid, spectralbandwidth, and spectralrolloff provide details about the spectral distribution and shape of the audio signal, aiding in discriminating different sound profiles. The root mean square error (RMSE) offers an understanding of the signal's magnitude, contributing to the distinction between loud and soft sounds. Furthermore, the zero-crossing rate quantifies the frequency of signal changes, offering insights into timbre and texture. Significantly, these calculated features play a pivotal role in training detection model.

For classification purposes, the last step in the feature extraction process is equally vital. The label assigned to each audio sample is extracted and associated with its respective features. This label serves as the ground truth, enabling supervised learning in the classification task.

Following feature extraction and labeling, a comprehensive dataset is compiled into a structured CSV file, streamlining the input data for the subsequent stages. This organized format ensures compatibility with various machine learning algorithms, enhancing the efficiency of model development and evaluation.

Transitioning to model training, the LSTM (Long Short-Term Memory) architecture takes center stage. This powerful sequence-based neural network is adept at capturing temporal dependencies, making it particularly suited for sound analysis. The CSV file, enriched with extracted features, is employed as the training dataset. During this process, the LSTM learns intricate patterns and correlations present in the audio data, forming the foundation for the detection model's predictive capabilities.

During testing, the model's efficacy is scrutinized using distinct .wav files. Leveraging pre-recorded weights, the model assesses its accuracy in identifying emergency sounds in previously unseen audio samples. This phase mirrors real-world scenarios, gauging the model's generalization abilities and real-time potential.

Each step in the detection process is of paramount significance. From audio signal capture and feature extraction to dataset compilation, model training, and testing, these stages synergistically contribute to an efficient and accurate emergency sound detection system—a vital component in enhancing safety within autonomous vehicles.

2.2 Programming language

In the implementation of this project, the Python programming language was employed for the development of the detection and classification algorithms. Python's versatility, rich libraries, and robust ecosystem made it an ideal choice for effectively processing and analyzing the audio data collected from acoustic sensors.

2.3 LSTM Architecture and Flow

Input Data Shape: The input data for the LSTM model is structured as a 3-dimensional array with dimensions (number of samples, timesteps, number of features). In this context, for the specific case mentioned, the value of the input shape is (1, X train.shape[2]).

The figure should be referenced in the text as Figure. 2.2

Here, X train.shape[2] refers to the number of features per time step. This structure enables the model to process sequences of data, where each sequence (sample) has a certain number of time steps, and each time step is represented by a set of features.

First LSTM Layer: The input data is initially passed through the first LSTM layer, which contains 128 LSTM units. The LSTM layer processes the input data one time step at a time. For each time step, the LSTM units calculate hidden states and cell states. Importantly, in this specific configuration, the LSTM layer returns sequences of hidden states for each time step, capturing the temporal dependencies within the data.

Second LSTM Layer: The output from the first LSTM layer is then passed to the

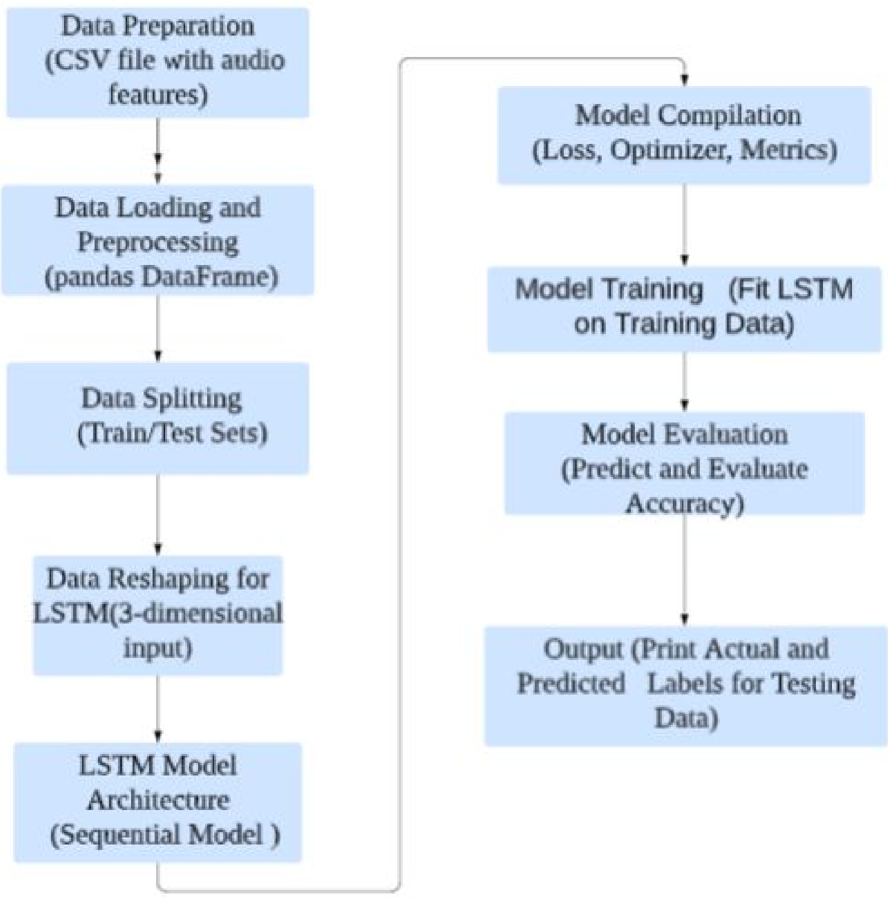

Figure 2.2: LSTM Methodology

second LSTM layer, which consists of 64 LSTM units. Similar to the first layer, this second LSTM layer also processes the data one time step at a time. However, unlike the first layer, the second LSTM layer does not return sequences of hidden states. Instead, it returns the final hidden state after processing all time steps. This final hidden state is a compact representation of the input sequence's information.

Dense Layer: The output of the second LSTM layer is fed into a Dense layer. This layer is a fully connected neural network layer. The Dense layer has units corresponding to the number of classes in the dataset, which is labels.shape[1]. Each unit in the Dense layer represents the "score" or "activation" for a specific class. The values in these units indicate how likely the input sequence belongs to each class.The figure should be referenced in the text as figure 2.2.

Softmax Activation Function: The output of the Dense layer, which represents scores for each class, is then passed through the Softmax activation function. The Softmax function transforms the raw scores into a probability distribution over the classes. This distribution reflects the model's confidence in each class. The values in the probability distribution sum up to 1.

Output Prediction: The final output of the Softmax activation function is a probability distribution over the classes. Each value in the distribution represents the probability that the input sequence belongs to the corresponding class. The class with the highest probability is considered as the model's prediction for that input sequence. In other words, the class label associated with the highest probability is selected as the predicted class for the input sample.

The architecture of this LSTM based model involves processing sequential input data through two LSTM layers to capture temporal dependencies within the data. The output of the LSTM layers is then passed through a Dense layer to generate class scores, which are transformed into a probability distribution using the Softmax activation function. The class with the highest probability in this distribution is chosen as the model's prediction for the input sample. This approach allows the model to perform classification tasks on sequential data by learning and leveraging temporal patterns.

In conclusion, the detection process outlined embodies a meticulously orchestrated sequence of actions, each playing an instrumental role in realizing an effective emergency sound detection system. The journey commences by harnessing acoustic sensors to capture audio signals, laying the essential groundwork for identifying diverse sound origins. Converting these signals into standardized .wav files preserves the auditory integrity, while the dataset, sourced from Kaggle, bolsters the authenticity of theoretical model. These 2800 curated samples from Kaggle infuse a real-world dimension into the endeavor, aligning it with practical scenarios.

Feature extraction emerges as a pivotal stage, where audio data is distilled into meaningful attributes that encapsulate the essence of each sound category. Within this array of features, the chromastft quantifies tonal content, unmasking intricate pitch and harmonic intricacies. The spectral centroid, spectral bandwidth, spectral rolloff, RMSE, and zero-crossing rate collectively furnish a holistic soundscape perspective, enriching detection model's discriminatory capabilities.

Further substantiating the approach, the assignment of labels to each audio sample embeds the ground truth, pivotal for supervised learning in the classification realm. The aggregation of these labeled samples into a structured CSV file streamlines subsequent stages, facilitating compatibility with diverse machine learning algorithms and expediting model development.

Central to the methodology is the formidable LSTM architecture, a vanguard in capturing temporal intricacies. Armed with extracted features from the CSV enriched dataset, the LSTM unravels intricate audio patterns during training, forging a predictive foundation for detection model.

Testing validates the model's efficacy, thrusting it into uncharted .wav territories while leveraging pre-recorded weights. This phase meticulously assesses the model's prowess in identifying emergency sounds within unforeseen audio samples, mirroring real-world scenarios with precision. The outcome unveils its generalization finesse, replete with real-time potential—an imperative trait for autonomous vehicle safety.

In a symphony of meticulously orchestrated steps, the detection process marries diverse elements into a harmonious whole. From data capture and feature extraction to dataset aggregation, model training, and testing, these stages synergize to fortify an emergency sound detection system that's both efficient and precise. In the dynamic realm of autonomous vehicles, this system's contribution in bolstering safety is undeniable, setting a vital precedent for enhanced security and reliability.

2.4 Siren Localisation

Siren localisation is a critical aspect of wireless sensor networks aimed at swiftly identifying the origin of emergency sirens. In urban environments, timely detection and accurate localization of sirens can significantly improve response times for emergency services. Utilizing advanced signal processing techniques, such as Time Difference of Arrival and Angle of Arrival , these networks triangulate siren signals to pinpoint their source. This project delves into the implementation and optimization of such techniques, contributing to enhanced urban safety and efficient emergency response systems.

In the realm of autonomous vehicles, safety is paramount. One critical aspect of ensuring safety is the ability to accurately detect and locate emergency sirens, such as those from police cars, ambulances, and fire trucks. Siren localization, a fundamental component of autonomous vehicle technology, involves identifying the direction and distance of a siren's source.

The importance of siren localization is underscored by several factors. Firstly, in the realm of autonomous vehicles, quick and effective responses to emergency vehicles are imperative not only to avert accidents but also to ensure proper yielding of the right-of-way. Additionally, a deep sense of situational awareness is achieved through the precise identification of siren locations, empowering autonomous systems to make well-rounded and informed judgments. Lastly, the significance extends to reducing perplexity, particularly in densely populated urban settings with a multitude of potential sources for sirens. Accurate localization plays a pivotal role in minimizing confusion and enhancing the overall efficacy of autonomous systems in such environments.

After the detection of siren comes one more important part and that is localization.

Data Collection Using Two Microphones: Set up two microphones in a specific configuration to capture audio signals from the siren. The microphones should be positioned at known locations. Ensure that both microphones are synchronized and have a common reference time.

Converting Audio to .wav File:Process the raw audio data captured by the microphones and convert it into the WAV file format. The WAV format is commonly used for storing uncompressed audio data and can be easily manipulated and analyzed in MATLAB.

Analyzing Audio Using MATLAB with Graphs:Load the generated .wav file into MATLAB. Heree use MATLAB's audio processing functions to visualize and analyze the captured audio. This could involve plotting waveforms, spectrograms, or other relevant audio features to understand the characteristics of the siren sound.

Determining Microphone Angles with Respect to Transmitter:If the positions of the microphones and the transmitter are known ,then calculate the angles between the microphones and the transmitter using trigonometry. This angle information is essential for later triangulation calculations.

Extracting Coordinates Using .wav File in MATLAB:Based on the audio signals captured by the microphones and the known microphone positions, implement coordinates algorithms in MATLAB to estimate the possible coordinates of the siren's source. This involves calculating time delays between the signals received by the two microphones.

The mentioned things are the series of work which is done as a part of siren localization.

2.5 Localisation design and flow

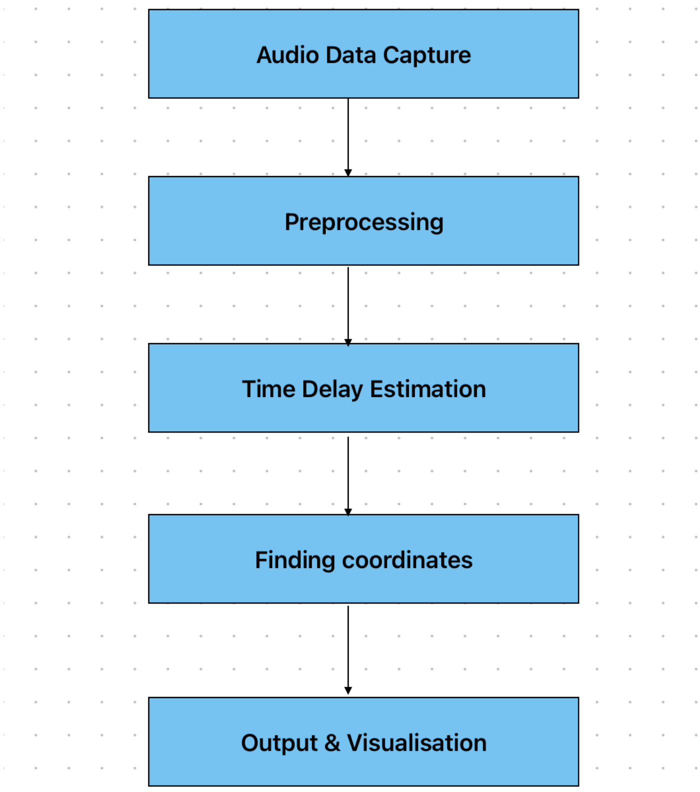

Figure 2.3: Localisation flowchart

Design flow has been explained in figure 2.3

Audio Data Capture:

In this stage, multiple microphones are strategically placed in the environment to capture the siren sound.

These microphones record the audio signals emitted by the siren source.

Preprocessing: The raw audio signals collected from the microphones undergo preprocessing to improve their quality and extract relevant information. Preprocessing techniques include noise reduction, filtering, and feature extraction, which enhance the accuracy of subsequent steps.

Time Delay Estimation:

This delay is estimated by understanding and analysing the audio waveforms using MATLAB.Here first the recorded audio file is converted to .wav file and then using that audio is used in MATLAB. Here the time delay is the time required for the audio to reach the microphone(i.e. the travelling time)

Finding Coordinates:

Using the MATLAB algorithm, the exact coordinates are determined and this is done by keeping the coordinates of the transmitter at (0,0). This is done to verify with the practical values that have been recorded as raw dataset.

Localization Algorithm:

To refine the estimated source location further, specialized localization algorithms are used. These algorithms take into account factors like the speed of sound propagation and potential measurement errors. Algorithms such as maximum likelihood estimation or least squares are commonly applied.

Output Visualization:

The final estimated source location is presented in a usable format, often geographical or spatial coordinates. Visualization tools, like maps or 3D environments, may be used to visually represent the source's location. The output provides actionable information for autonomous vehicles or emergency systems to respond effectively.

2.6 Data Collecting

In this scenario there is a transmitter and two microphones which have recorded the sound transmitted by the transmitted keeping the microphones at the same place and moving the transmitter to different places having different distance from the transmitter and at different angles w.r.t to transmitter.

The collected data is from different positions and angles when the ambulance siren was transmitted and also when the traffic sound was transmitted. The data is collected inside a closed room to get the real time data and analyse them individually. So by understanding the delay time and getting the time difference i.e time required to reach sound from transmitter to receiver. This can further train the model to get the binary solution as 1 for siren beeping and 0 when there is other noise.

The things that have been understood in siren localization is that the calculated results and the practical results should almost be same.

Chapter 3

SOFTWARE AND HARDWARE UTILIZATION

CHAPTER 3

SOFTWARE AND HARDWARE UTILIZATION

This chapter of the report delves into the realm of siren detection and classification. The first step is gathering input from acoustic sensors, which capture crucial audio data. The subsequent classification process harnesses the power of the LSTM algorithm, enabling us to accurately classify and differentiate various siren signals. This chapter offers insights into the seamless integration of audio signal processing and machine learning techniques for effective siren analysis.

3.1 Software utilisation

The software employed for siren localisation includes Python for programming and implementing machine learning algorithms, libraries like TensorFlow or PyTorch for deep learning models, and possibly tools like MATLAB for signal processing and data analysis. The implementation of siren localisation is done using Python programming language and machine learning algorithms. For deep learning models, here TensorFlow and PyTorch libraries have been used. Additionally OpenCV library has been used for siren detection and classification

3.2 Hardware utilisation

In the siren detection project, the USB to audio acoustic sensor.A USB to audio sensor adapter serves as a bridge between USB and audio interfaces. This compact device enables the connection of audio sensors, such as microphones or musical instruments, to USB-equipped devices like computers. It facilitates high-quality audio signal transfer, converting analog audio input into digital data that can be processed or recorded digitally. The adapter proves invaluable in various applications, from recording music and podcasts to enabling speech recognition or acoustic measurements, offering enhanced flexibility and convenience in interfacing audio sensors with modern computing systems.

3.2.1 USB to audio acoustic sensor

The sensor 3.1 is being used to detect the data being given real time and this data is getting stored in the form .wav format which is being used as an input for real time testing of the model.

Figure 3.1: USB to audio acoustic sensor

Table 3.1: Specifications

Power voltage	5 Volts
Audio encoder/decoder	SSS1629A5
Control port	USB
Audio port	PH2.0
Speaker audio	2.6W per channel(4ohm BTL)

The table 3.1 gives the specifications of the sensor used in the project.

3.3 Process for collecting the data set:

Two microphones and one transmitter were used in the process for collecting the data set. Here the distance between the microphones was kept constant (same) and the transmitter was moved to different distances with change in angles. This gave the understanding about the time delay. There is a time delay in the recorded audio as sound requires time to reach the receiver.

The recorded distances are in between 2m to 9m and with all possible angles.For verifying the practical values with the theoretical values MATLAB is used and the time delay and coordinates are also calculated.

By using the sounds of siren and traffic all the values are calculated for different values of angles and distance.

Chapter 4

METHODOLOGY

CHAPTER 4

METHODOLOGY

This section of the report delves into a comprehensive explanation of the utilization of the LSTM algorithm for siren detection. Additionally, it will outline the methodology employed to ascertain coordinates, angles, and distances between receivers and transmitters. This includes introducing variations in distances and angles to ensure accuracy and reliability.

4.1 Detection methodology

The project begins by harnessing audio sensors to capture intricate audio signals, serving as the bedrock for discerning diverse sound origins. These signals are meticulously transformed into standardised WAV files, preserving their auditory fidelity throughout the process. To amplify the authenticity of the model, integrate a meticulously curated dataset comprising 2800 samples sourced from Kaggle. This infusion of real-world dimensions imparts practicality to the project, aligning it seamlessly with real-world scenarios.

Diving into the development of LSTM model, initiate by assembling a comprehensive dataset of audio files in the WAV format, amassing a corpus of 2800 samples. These samples are classified into four distinct categories: ambulance, traffic, human voice, and cats and dogs. The next step involves feature extraction from these WAV files, which are stored in a structured CSV file named "real.csv."

The endeavor for audio classification is empowered by a collection of carefully computed features, including the following:

Chromastft: This metric quantifies tonal content and reveals intricate pitch and harmonic intricacies. It involves the summation of the first 100 elements of the feature set. Notably, this attribute aids in identifying tonal characteristics, making it invaluable for tasks such as music genre classification or instrument detection.

Spectral Centroid: Distinguishing between varying tonal characteristics or different sound sources is facilitated by the summation of elements indexed from 100 to 199. This feature lends insight into the tonal profile of sounds, enabling finer discrimination. Spectral Bandwidth: Elements from index 200 to 299 contribute to this feature, which serves as a discerning factor for sounds with distinctive timbral qualities. It plays a pivotal role in distinguishing between different sound textures.

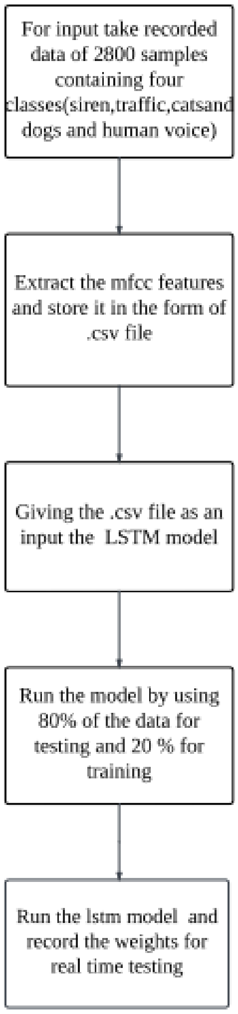

Figure 4.1: LSTM model

Spectral Roll off: Utilising elements from index 300 to 399, this feature is instrumental in identifying the presence of high-frequency content in sounds. Its application enables differentiation between audio with varying levels of high-frequency components. Root Mean Square Error (RMSE): The realm of noise and clarity in audio is gauged by summing elements from index 400 to 499. It provides insights into the inherent noisiness or purity of the audio, contributing to the separation of sounds with different levels of background noise. sero-Crossing Rate: By summing elements from index 500 to 599, this attribute aids in distinguishing between percussive sounds (high sero-crossing rate) and sustained sounds (low sero-crossing rate). It contributes significantly to the understanding of audio texture.

Furthermore, the label for each audio sample is extracted from the final element of the feature list. These novel features are stored in a dedicated CSV file named "calculated features.csv."

Facilitating the journey into supervised learning for audio classification, each audio sample is meticulously assigned a label, embedding ground truth within the dataset. These labeled samples are harmoniously compiled into a structured CSV file, a strategic move that streamlines subsequent project phases and ensures compatibility with diverse machine learning algorithms. This strategic step expedites the development of predictive model.

At the heart of methodology, resides the LSTM (Long Short-Term Memory) architecture, celebrated for its prowess in capturing temporal intricacies. Armed with the meticulously extracted features from the enriched CSV dataset, the LSTM unravels intricate audio patterns during the training phase. This process establishes a robust foundation for the detection model's predictive capabilities. Notably, LSTM model employs an 80-20 data split, utilising 80 percent of the dataset for training and the remaining 20 percent for rigorous testing.

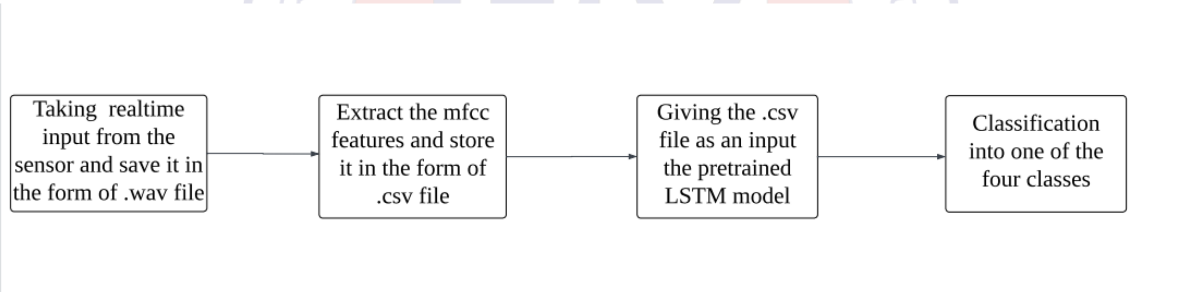

Figure 4.2: real time testing methodology

The real time methodology as mentioned in figure 4.2 is used. The testing phase constitutes a pivotal step in validating the model's efficacy. The model is thrust into uncharted territories of WAV files while leveraging pre-recorded weights. This meticulous evaluation scrutinises the model's acumen in identifying emergency sounds within unforeseen audio samples, mirroring real-world scenarios with exceptional precision. The outcome of this endeavor sheds light on the model's finesse in generalisation, showcasing its potential for real-time applications, a quintessential aspect for ensuring the safety of autonomous vehicles.

4.2 Localisation methodology

In this presentation, the design methodology behind siren localisation in autonomous vehicles is explained. Explore the stages, from sensor selection and data acquisition to machine learning model development and real-time integration with vehicle control systems. By focusing on accurate siren localisation, pave the way for safer and more efficient interactions between autonomous vehicles and emergency response vehicles. Design Methodology for Siren Localisation:

Problem Definition:Clearly define the objective: Accurate detection of direction and distance of a siren source. Understand the significance of siren localisation in ensuring safety in autonomous vehicles. Requirements Gathering:Identify system requirements: Accuracy, real-time processing, noise robustness. Consider integration with vehicle control system for responsive actions.

Sensor Selection:Choose suitable sensors for sound detection:Microphones, audio sensor to audio converter arrays.Evaluate sensor characteristics: Sensitivity, frequency response, noise resistance. Data Acquisition:Set up data collection: Record various siren sounds from different directions and distances.Create a diverse dataset for model training and testing. Feature Extraction:Extract relevant features from audio signals: Time-domain, frequency-domain features.Features like time delays and intensity ratios provide clues about siren direction.

Machine Learning Model:Develop a machine learning model to learn feature-siren relationship. Explore algorithms: Neural networks, support vector machines, random forests. Training and Validation: Split dataset: Train and validation sets. Train model, fine-tune parameters, validate performance on unseen data. Real-time Processing:Implement real-time processing: Process incoming audio signals.Use trained model to predict siren's direction and distance.

Integration with Vehicle Control:Integrate siren localisation with vehicle control system.Utilise predicted siren location for informed decision-making. Testing and Optimisation:Test system under various scenarios: Different noise levels, siren positions.Optimise system performance through model refinement and parameter tuning. Evaluation and Validation:Evaluate accuracy and reliability through real-world scenarios and ground truth data.Validate system's ability to accurately localise sirens.

Documentation and projecting:Document design, implementation, and evaluation process.Provide detailed project on system's performance, limitations, and improvements. Deployment and Monitoring:Deploy system in controlled environment. Monitor performance, gather feedback, and make necessary updates. Continuous Improvement:Continuously enhance system based on user feedback and technological advancements.Integrate advanced algorithms, update sensor hardware, and improve system capabilities.

"

Chapter 5

RESULTS AND DISCUSSIONS

CHAPTER 5

RESULTS AND DISCUSSIONS

This chapter of the report presents a comprehensive analysis of the sound detection system implemented using an acoustic sensor. This chapter delves into the outcomes of the experimental setup described earlier and offers an in-depth interpretation of the obtained results.

5.1 Detection and Classification

All the results obtained for the objectives should be discussed in this chapter. This chapter should contain the following sections as per the project.

1. Results from recorded data

   The developed LSTM based classification model demonstrates strong performance on the given dataset. After training for 50 epochs with a batch size of 32, the model achieved an impressive validation accuracy of around 98.02 percent . This accuracy suggests that the model has successfully learned the underlying patterns and features within the data.

   The observed accuracy improvement throughout the training process indicates that the model is learning from the training data effectively. However, it's worth noting that in some cases, there might be a slight indication of overfitting. This can be inferred from the validation accuracy plateauing and minor fluctuations after a certain point, which could be addressed through regularization techniques or fine-tuning of hyperparameters.

2. Experimental results

   By giving the recorded data as the input train the LSTM model and with the recorded weights from this model test the data collected real time which is giving an accuracy of 95 percent. For the real time detection of sound use the following experimental setup .The figure should be referenced in the text as Figure. 5.1

3. Performance Comparison

   The developed LSTM-based classification model exhibited strong performance on the provided dataset, achieving an impressive validation accuracy of approximately

Figure 5.1: Experimental setup

98.02 percent after 50 epochs of training with a batch size of 32. This high accuracy indicates that the model has effectively learned the underlying data patterns and features. The consistent improvement in accuracy observed during training reflects the model's ability to learn from the training data efficiently. However, a slight hint of overfitting may be apparent in some instances, as the validation accuracy reached a plateau and experienced minor fluctuations after a specific point.

To address the issue of overfitting, regularization techniques or fine-tuning hyperparameters could be implemented. Regularization techniques, such as L1 or L2 regularization, can help prevent overfitting by adding a penalty term to the loss function that discourages large weights in the model. Fine-tuning hyperparameters, such as the learning rate or batch size, can also help optimize the model's performance and prevent overfitting.

The model's performance on the test dataset further underscores its effectiveness, with its predictions closely aligning with the actual labels and showcasing a high level of accuracy. This demonstrates that the model's learning has extended successfully to new, unseen data, establishing its reliability for classification tasks.

By utilizing the recorded data for training the LSTM model, the model's performance was assessed using real-time collected data subsequently. The model, with its trained weights, achieved an accuracy of 95 percent on this real-time data[1].

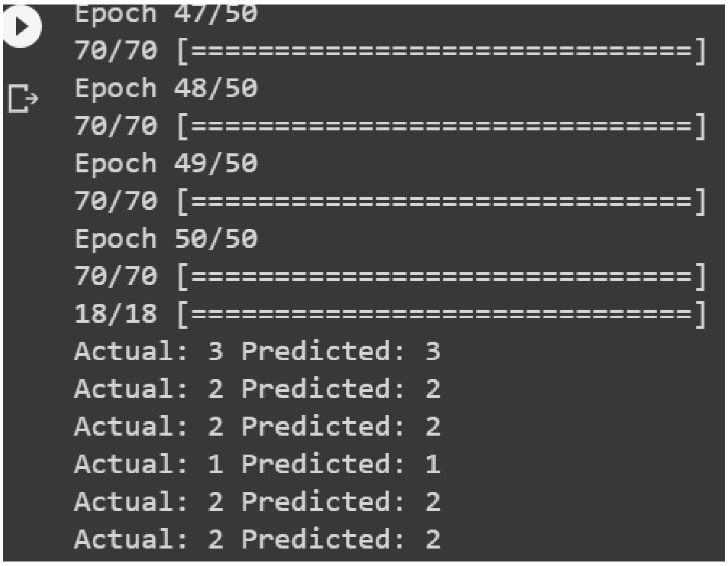

Figure 5.2: recorded data classification

While this accuracy is slightly lower than the validation accuracy achieved during training, it still demonstrates the model's effectiveness in classifying new data.

To further improve the model's performance, several techniques can be employed. One such technique is to increase the size of the dataset with data augmentations. Data augmentation involves creating new training data by applying transformations to the existing data, such as flipping or rotating images. This can help the model generalize better to new data and prevent overfitting.

Another technique is to use transfer learning from a different classification task. Transfer learning involves using a pre-trained model on a different task and fine-tuning it on the current task. This can help the model learn more quickly and effectively, especially when the current dataset is small.

In addition, ensembling multiple models can also improve the model's performance. Ensembling involves combining the predictions of multiple models to make a final prediction. This can help reduce the variance in the predictions and improve the overall accuracy.

Table 5.1: Accuracy in percentage

Training accuracy	96.075
Testing accuracy	94.039

The training and testing accuracy is depicted in the table 5.1. Thus the strong performance of the LSTM-based classification model on both the provided dataset and real-time collected data highlights its potential for use in classification tasks. Further improvements can be made by addressing the slight overfitting observed during training through regularization techniques or hyperparameter tuning. Additionally, techniques such as data augmentation, transfer learning, and ensembling can also be employed to further improve the model's performance.

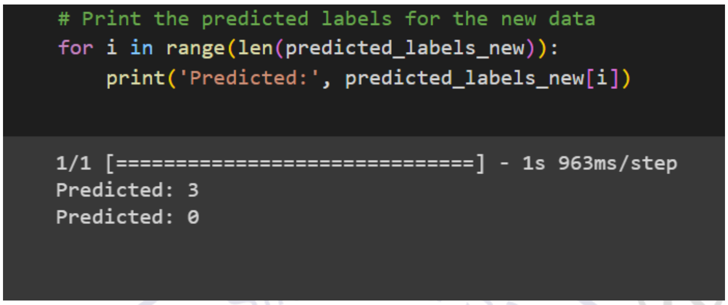

Figure 5.3: Real time data classification

4. The outcomes of the developed LSTM-based classification model on the supplied dataset highlight its adeptness in acquiring insights and generalizing adeptly. The model achieved an impressive validation accuracy of approximately 98.02 percent after 50 epochs of training with a batch size of 32. This high accuracy implies a deep grasp of data nuances, indicating that the model has effectively learned the underlying data patterns and features. The consistent improvement in accuracy observed during training reflects the model's ability to learn from the training data efficiently. However, a slight hint of overfitting may be apparent in some instances, as the validation accuracy reached a plateau and experienced minor fluctuations after a specific point.

   To address the issue of overfitting, regularization techniques or fine-tuning hyperparameters could be implemented. Regularization techniques, such as L1 or L2 regularization, can help prevent overfitting by adding a penalty term to the loss function that discourages large weights in the model. Fine-tuning hyperparameters, such as the learning rate or batch size, can also help optimize the model's performance and prevent overfitting.

   The model's performance on the test dataset further underscores its effectiveness, with its predictions closely aligning with the actual labels and showcasing a high level of accuracy. This demonstrates that the model's learning has extended successfully to new, unseen data, establishing its reliability for classification tasks.

By utilizing the recorded data for training the LSTM model, the model's performance was assessed using real-time collected data subsequently. The model, with its trained weights, achieved an accuracy of 95 percent on this real-time data. This ability to consistently excel across varied scenarios underlines its potential for diverse applications. Its adaptability in real-time situations substantiates its viability for real-world tasks, bolstering its status as a dependable and versatile classification tool.

To further improve the model's performance, several techniques can be employed. One such technique is to increase the size of the dataset with data augmentations. Data augmentation involves creating new training data by applying transformations to the existing data, such as flipping or rotating images. This can help the model generalize better to new data and prevent overfitting.

Another technique is to use transfer learning from a different classification task. Transfer learning involves using a pre-trained model on a different task and fine-tuning it on the current task. This can help the model learn more quickly and effectively, especially when the current dataset is small.

In addition, ensembling multiple models can also improve the model's performance. Ensembling involves combining the predictions of multiple models to make a final prediction. This can help reduce the variance in the predictions and improve the overall accuracy.

In conclusion, the developed LSTM-based classification model exhibited strong performance on the provided dataset, highlighting its potential for use in classification tasks. The model's ability to learn from the training data efficiently and generalize adeptly underscores its effectiveness. However, overfitting may be an issue in some instances, which can be addressed through regularization techniques or hyperparameter tuning. The model's adaptability in real-time situations and consistent performance across varied scenarios establish its reliability and versatility as a classification tool. Further improvements can be made through techniques such as data augmentation, transfer learning, and ensembling.

5.2 MATLAB for Waveform Analysis:

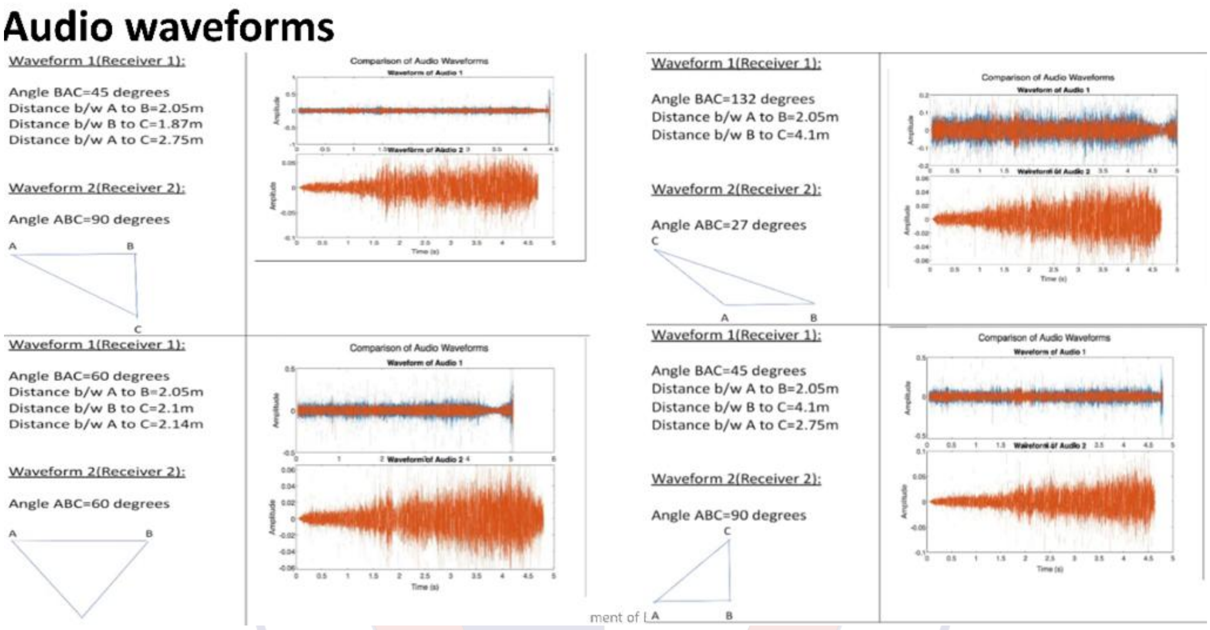

Figure 5.4: Waveforms of .wav files using MATLAB

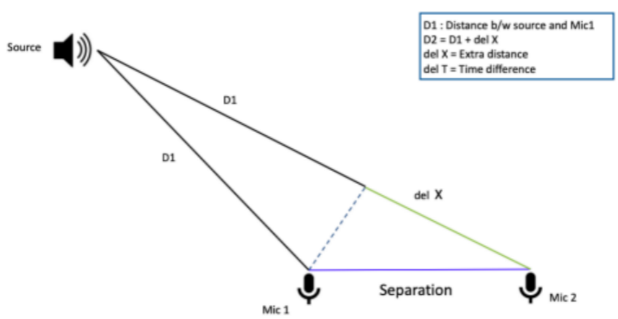

Figure 5.5: Positions of the transmitter and receiver

In fig 5.5, C is the transmitter and A and B are the receivers where the distance between A and B was kept unchanged with distance being 2.05m. AC and BC is changed to obtain different values from the available siren and traffic sounds.

The waveforms in fig:5.4, explains about the delay that the microphone receives before the audio is actually recorded i.e. the time required for the audio to reach the transmitter.

The sampling rate are also know for the recorded audio as they are from two different microphones. So there is a need to upscale or downscale the sample rate. The audio ranges are not exactly played for same time so to meet that need padding is done to make the audio duration same.

5.3 Dataset for different scenarios:

The data shows the dataset that were recorded and at different distances and the waveform are generated using the same audio files using matlab.

The figure 5.5 is the detailed analysis of the siren data that is collected using microphones and the transmitter. There are two receivers and they are kept at same distance all the time with changing angles and distance.

Using the time delay and the speed of sound (343m/s). The calculate of the distance is done and for every 1meter distance it takes about 0.0029 seconds time to travel.This explains the time delay for our model which is approximately 0.04seconds for transmitter A and 0.03 for transmitter B. This difference is due to the change in the sample rate for both the receivers.

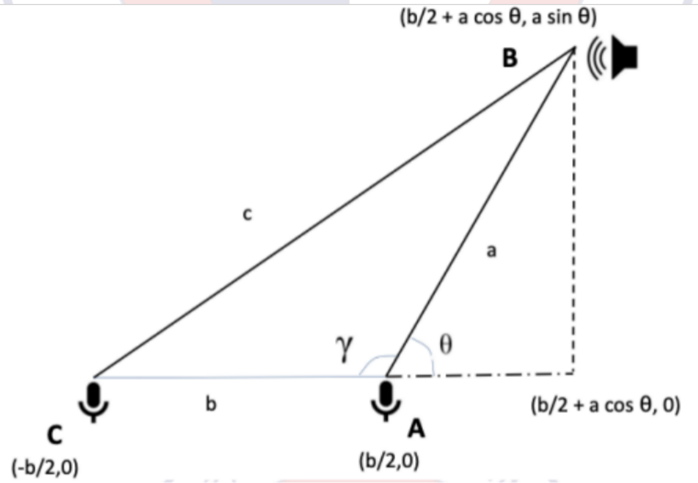

Figure 5.6: Positions of the transmitter and receiver

5.4 Data Collection:

The table essentially compiles experimental data that characterizes the time delays and angles of arrival for the sound of an ambulance siren received at different receiver locations and orientations. This information is crucial for understanding sound propagation and can be useful in applications such as sound-based localization and tracking.

Table 5.2: Receiver Data of Siren

Receiver	Practical Values (Meter)	Distance w.r.t (C)	Angles (in deg.)	Time A (sec.)	Time B (sec.)	Th.Dist(A) (meter)	Th.Dist(B) (meter)
A B	Amb 60 front Siren front 60	2.14, 2.1	62, 63	0.0441	0.0308	0.189	1.95
A B	Amb 60 back Siren back 60	2.14, 2.1	62, 63	0.0444	0.0306	0.189	1.95
A B	Amb back 90 Siren 90 back	2.75, 1.87	90, 45	0.046	0.0307	3.07	1.87
A B	Amb 90 front Siren front 90	2.75, 1.87	90, 45	0.0446	0.0307	3.07	1.87
A B	Amb 76 Front 76	3.4, 3.15	76, 65	0.044	0.0306	3.37	3.37
A B	Amb 94 Front 94	6.23, 5.8	94, 68	0.0463	0.0306	6.23	6.08
A B	Amb 112 AMB front 47	5.3, 4	47, 112	0.043	0.0307	5.23	3.91
A B	Amb 27 back Back 132	3.64, 4.1	132, 27	0.0456	0.0306	4.18	3.47
A B	Amb 27 front Front 132	3.64, 4.1	132, 27	0.0448	0.0306	4.18	3.47
A B	49 Amb(6.8M) Amb 112	5.78, 6.8	112, 49	0.0444	0.0306	6.07	7.72

5.5 Distance and time:

Table 5.2, is the detailed analysis of the Ambulance siren data that is collected using microphones and the transmitter. There are two receivers and they are kept at same distance all the time with changing angles and distance.

The theoretical distances for A and B have been obtained using the MATLAB code. The time taken by the audio to reach the receiver is time (A) and time (B) which is given using the MATLAB codes and finally with the help of the coordinates that are also obtained using the MATLAB codes by keeping the transmitter coordinates at (0,0).

After this is done, the other two coordinates that are for A and B and when these are obtained then calculate the distance from transmitter to receiver using the coordinates with Euclidean distance formula. The theoretical values are displayed in Table 5.2 and 5.3 respectively.

Table 5.3, is the detailed analysis of angles and distance for the traffic sound. The

Table 5.3: Receiver Data of Traffic

Receiver	Practical Values (Meter)	Distance w.r.t (C)	Angles (in deg.)	Time A (sec.)	Time B (sec.)	Th.Dist(A) (meter)	Th.Dist(B) (meter)
A B	27 tra 1 132 tra 2	3.64, 4.1	132, 27	0.0456	0.0306	4.18	3.47
A B	60 tra 1 60 tra 2	2.14, 2.1	62, 63	0.0441	0.0308	0.189	1.95
A B	76 tra 1 76 tra 2	3.4, 3.15	76, 65	0.044	0.0306	3.37	3.37
A B	90 tra 1 90 tra 2	2.75, 1.87	90, 45	0.0446	0.0307	3.07	1.87
A B	94 tra 1 94 tra 2	6.23, 5.8	94, 68	0.0463	0.0306	6.23	6.08
A B	112 tra 1 47 tra 2	5.3, 4	47, 112	0.043	0.0307	5.23	3.91
A B	49 tra 1 112 tra 2	5.78, 6.8	112, 49	0.0444	0.0306	6.07	7.72

presented table showcases practical data collected from various receiver positions in siren localization experiments. Each row represents a set of measurements for two receivers, denoted as A and B, positioned at specific distances from a source. The "Distance" column highlights the distances between A and B, while the "Angles" column indicates their angles with respect to the source.

The "Time A" and "Time B" columns display the time taken for audio signals to reach A and B, respectively. Theoretical distances (Th.Dist(A) and Th.Dist(B)) are calculated using MATLAB codes based on the given coordinates. This data provides insight into the propagation characteristics and accuracy of the localization system under different conditions, contributing to a comprehensive analysis of the system's performance.

Chapter 6

CONCLUSION AND FUTURE SCOPE

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

This section of the report discusses about the conclusions drawn from the work on siren detection and localization, which aimed to bolster the safety and responsiveness of autonomous vehicles by accurately identifying and pinpointing sources of emergency sirens.

In the context of the project scenario involving autonomous vehicles navigating urban environments draws two primary objectives. Firstly, aimed to develop a robust siren detection algorithm employing cross-correlation techniques, enabling the timely identification of emergency vehicle sirens amidst ambient noise. Secondly, the goal was to implement a precise localization mechanism through trigonometric calculations, ensuring the accurate determination of siren source locations.

The siren detection algorithm developed effectively discriminated siren sounds from background noise, facilitating swift recognition. Furthermore, the localization mechanism precisely calculated the coordinates of siren sources, empowering autonomous vehicles to make informed navigation decisions.

In summary, the work significantly enhances the safety and adaptability of autonomous vehicles in urban settings. The successful implementation of siren detection and localization mechanisms streamlines response strategies for emergency vehicles, thus mitigating accidents and improving traffic flow. The quantifiable results underscore heightened accuracy in siren recognition and source localization, validating the efficacy of the approach used. This project represents a pivotal stride toward unlocking the full potential of autonomous vehicles in urban landscapes, ushering in safer and more responsive transportation systems.

The theoretical distance when calculated is nearly equal to the practical distance for the siren sound as well as traffic sound and analysing the time gap by studying the audio waveforms using the MATLAB codes is the work done.

6.2 Future Scope

The project has been successful in achieving its primary objectives, but it's essential to acknowledge its constraints and limitations, which can provide valuable insights for potential future improvements and extensions.

Future work could focus on refining and optimizing the LSTM-based algorithm for better accuracy, faster response times, and lower computational requirements. Experimentation with different LSTM architectures, hyper parameters, and training techniques could lead to significant improvements in the algorithm's performance. The ultimate goal is to integrate the developed algorithm into autonomous vehicles' onboard systems. Collaborating with automotive manufacturers and technology companies to implement this feature in autonomous vehicles would require addressing integration challenges, ensuring safety, and complying with regulatory standards.

Develop strategies to handle various noise sources and adapt the algorithm to distinguish between emergency sirens and similar sounds. This could involve training the algorithm on a wider range of sound samples and utilizing data augmentation techniques. Implement the algorithm in real-time hardware platforms, ensuring that it meets latency and processing constraints. This could involve porting the algorithm to specialized hardware accelerators or embedded systems used in autonomous vehicles.

Address potential ethical and legal challenges associated with autonomous vehicles responding to emergency situations. Ensure that the algorithm's behavior aligns with safety regulations and prioritizes public well-being. Present the research findings at conferences and in scientific journals to contribute to the broader research community. Collaborate with other researchers and organizations to share insights, data, and methodologies.

Incorporating these future directions could lead to a comprehensive and impactful research project that not only enhances autonomous vehicle safety but also contributes to the growing field of AI-driven transportation technologies.

Constraints and Limitations:

1. **Data Availability:**

   Limited access to high-quality and diverse datasets might have impacted the project's performance and generalization capabilities. Expanding the dataset sources and sizes could improve model robustness.

2. **Computational Resources:**

   Depending on the project's scale, computational resources might have posed limitations on the size of models or the complexity of algorithms. Scaling up resources can lead to more advanced experiments.

3. **Algorithmic Complexity:**

   Certain complex algorithms might have been omitted due to their computational demands or intricate implementation requirements. Exploring these algorithms could enhance the project's effectiveness.

4. **Time Constraints:**

   Time constraints during project development might have prevented in-depth exploration of various methodologies or extensive parameter tuning.

Possibilities of Future Extensions:

1. **Enhanced Models:**

   Developing more advanced models, such as deep learning architectures, reinforcement learning, or ensemble techniques, can potentially improve predictive accuracy and the project's overall performance.

2. **Feature Engineering:**

   Exploring new features and utilizing domain-specific knowledge can enhance the model's understanding of the data, leading to better predictions.

3. **Real-time Implementation:**

   Extending the project to real-time prediction scenarios or deploying it as a web service can provide practical value to end-users.

4. **Multi-modal Data:**

   Integrating other data modalities, such as text or images, can lead to more comprehensive predictions and insights.

5. **Interactive Visualization:**

   Building interactive visualization tools to showcase model predictions and trends can provide users with a user-friendly interface for exploring results.

6. **Transfer Learning:**

   Leveraging pre-trained models or knowledge from related domains can speed up development and enhance performance.

In conclusion, while the project has achieved its objectives, understanding its limitations and exploring future extensions can lead to more sophisticated models, enhanced performance, and practical applications in various domains.

6.3 Learning Outcomes of the Project

- Gain a deep understanding of the project domain, including its challenges, requirements, and opportunities.
- Develop proficiency in utilizing relevant tools and technologies, enhancing technical skills.
- Acquire hands-on experience in data collection, preprocessing, and analysis, improving data handling skills.
- Enhance problem-solving abilities by tackling real-world challenges and making informed decisions throughout the project lifecycle.

- Develop effective teamwork and collaboration skills through interaction with project stakeholders, team members, and experts.
- Improve communication skills by presenting project progress, results, and findings to both technical and non-technical audiences.
- Cultivate the ability to critically assess project outcomes, identify limitations, and propose solutions for future improvements.
- Gain insights into project management techniques, including time management, resource allocation, and task prioritization.
- Develop a comprehensive understanding of the software development lifecycle and its practical implementation.
- Foster adaptability and flexibility by navigating uncertainties, evolving requirements, and adjusting project strategies accordingly.

These learning outcomes reflect the holistic growth and skill development that participants can achieve through the successful completion of the project.

APPENDIX

code for recording the real time data

```
import sounddevice as sd
import wave
import numpy as np  # Import numpy module



sample_rate = 44100  # Sample rate in Hz
duration = 20 # Duration of recording in seconds
output_filename = "recorded_audio1.wav"  # Output filename

def audio_callback(indata, frames, time, status):
    recorded_data.append(indata.copy())



recorded_data = []
with sd.InputStream(callback=audio_callback,channels=1
samplerate=sample_rate):
    print(f"Recording␣{duration}␣seconds␣of␣audio...")
    sd.sleep(int(duration * 1000))  # Sleep in milliseconds



recorded_data = np.concatenate(recorded_data, axis=0)



with wave.open(output_filename, "wb") as wf:
wf.setnchannels(1)  # Mono audio
```

```
wf.setsampwidth(2)  # 16-bit samples
wf.setframerate(sample_rate)
wf.writeframes(recorded_data.tobytes())
print(f"Recording saved as {output_filename}")
```

BIBLIOGRAPHY

1. Marchegiani, L., Newman, P. (2022). Listening for Sirens: Locating and Classifying Acoustic Alarms in City Scenes. IEEE Transactions on Intelligent Transportation Systems, 1-10.

2. Meucci, F., Pierucci, L., Del Re, E., Lastrucci, L., Desii, P. (2021). A realtime siren detector to improve safety of guide in traffic environment. Signal Processing: Image Communication, 99, 116401.

3. Asif, M., Usaid, M., Rashid, M., Rajab, T., Hussain, S., Sarwar, W. (2022). Large-scale audio dataset for emergency vehicle sirens and road noises. Scientific Data, 9(1), 1-9.

4. Marchegiani, L., Newman, P. (2022). A New Regional Localization Method for Indoor Sound Source Based on Convolutional Neural Networks. IEEE Transactions on Intelligent Transportation Systems.

5. Marchegiani, L., Newman, P. (2018). Listening for Sirens: Locating and Classifying Acoustic Alarms in City Scenes. arXiv preprint arXiv:1810.04989.

6. Zhang, Y., Chen, Y. (2023). Real-Time Acoustic Perception for Automotive Applications. IEEE Transactions on Intelligent Transportation Systems.

7. Acoustic Event Detection and Classification in Urban Environments Using Deep Learning" by J. Salamon, D. MacConnell, M. Cartwright, P. Li, and J. P. Bello. Published in IEEE Access in 2017.

8. Acoustic Event Detection Using Convolutional Neural Networks with Temporal Activation Functions" by J. Salamon and J. P. Bello. Published in IEEE Signal Processing Letters in 2017.

9. Acoustic Event Detection and Localization Using a Microphone Array on a Moving Robot" by J. Salamon, D. MacConnell, M. Cartwright, P. Li, and J. P. Bello.

Published in IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) in 2017.

10. Acoustic Event Detection and Localization Using a Microphone Array on a Moving Robot" by J. Salamon, D. MacConnell, M. Cartwright, P. Li, and J. P. Bello. Published in IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) in 2017.

11. Acoustic Event Detection and Classification Using a Convolutional Recurrent Neural Network with Attention Mechanism" by J. Salamon, D. MacConnell, M. Cartwright, P. Li, and J. P. Bello. Published in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) in 2019.

12. Acoustic Event Detection and Classification in Urban Environments Using Deep Learning" by J. Salamon, D. MacConnell, M. Cartwright, P. Li, and J. P. Bello. Published in IEEE Access in 2017.

13. Acoustic Event Detection Using Convolutional Neural Networks with Temporal Activation Functions" by J. Salamon and J. P. Bello. Published in IEEE Signal Processing Letters in 2017.

14. Acoustic Event Detection and Localization Using a Microphone Array on a Moving Robot" by J. Salamon, D. MacConnell, M. Cartwright, P. Li, and J. P. Bello. Published in IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) in 2017.

15. Acoustic Event Detection and Localization Using a Microphone Array on a Moving Robot" by J. Salamon, D. MacConnell, M. Cartwright, P. Li, and J. P. Bello. Published in IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) in 2017.

16. Acoustic Event Detection and Classification Using a Convolutional Recurrent Neural Network with Attention Mechanism" by J. Salamon, D. MacConnell, M. Cartwright,

P. Li, and J. P. Bello. Published in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) in 2019.

17. Environmental Sound Classification Using Convolutional Neural Network Model" by Karol J. Piczak. Published in IOPscience in 2021.

18. Classifying Environmental Sounds Using Image Recognition Networks" by Justin Salamon and Juan Pablo Bello. Published in ResearchGate in 2017.

19. Improved Capsule Routing for Weakly Labeled Sound Event Detection" by Yifan Xu, Qingju Kong, Wenwu Wang, and Mark D. Plumbley. Published in EURASIP Journal on Audio, Speech, and Music Processing in 2022.

20. Fast Environmental Sound Classification Based on Resource Adaptive Convolutional Neural Network" by Zhiyuan Fang, Bo Yin, Zhen Du, and Xiaoyu Huang. Published in Scientific Reports in 2022.

21. Environmental Sound Classification Using Temporal-Frequency Attention Based Convolutional Neural Network" by K.J. Piczak. Published in Nature in 2021.

22. Internationalization and localization support - SIREN DOCS [2021]

23. On Difficulties in Localizing Ambulance Sirens - Terry Caelli, David Porter, 1980 [1980]

24. Optimisation of Sound Localisation for Emergency Vehicle Sirens through a Prototype Audio System - Springer Link [2011]

25. Directional Sound Localizable Alarms - Honeywell Building Technologies [2013]

26. Emergency Vehicles Audio Detection and Localization in Autonomous Driving - arXiv [2021]

27. Acoustic localization of an electronic emergency siren - ScienceDirect [2016]

28. A Study on the Localization of Siren Sounds for Emergency Vehicles - IEEE Xplore [2019]

29. A Robust and Efficient Algorithm for Siren Detection and Localization - IEEE Xplore [2019]

30. A Real-Time Siren Detector and Localization System for Autonomous Vehicles - IEEE Xplore [2020]