SMART TRAFFIC MANAGEMENT FOR EMERGENCY VEHICLES USING YOLOV8

A Project Report

Submitted in partial fulfilment of the requirements for the
award of the degree of

BACHELOR OF TECHNOLOGY
In
ELECTRONICS AND COMMUNICATION ENGINEERING
By

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Mr./Miss……

Regd.No……..of final year B.E along with his/her batch mates submitted in partial fulfillment of the requirement of the award of Bachelor's degree in ELECTRONICS &COMMUNICATION ENGINEERING during the academic year 2020-2024.

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EXTERNAL EXAMINER **INTERNAL EXAMINER**

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DECLARATION

This is to certify that the project entitled **"SMART TRAFFIC MANAGEMENT FOR EMERGENCY VEHICLES USING YOLOV8 ALGORITHM"** which is submitted by **RONGALI GNANA PRASANNA (20B91A04K8), RAMINEEDI RAMA KRISHNA SAI SATWIK (20B91A04K6), PONALA RUPCHAND (20B91A04J4), PIGILAM SRIHAAS (20B91A04J1)** in partial fulfilment of the requirement for the award in degree in B.Tech in Electronics and Communication Engineering of S.R.K.R Engineering college, affiliated to JNTU KAKINADA. It comprises only our original work and due acknowledgement has been made in text to all other material used.

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CHAPTER 1
ABSTRACT

In the face of mounting urban traffic complexities, the swift and precise recognition of emergency vehicles, notably ambulances, stands as a critical factor in bolstering public safety and emergency responsiveness. This research delves into the nuanced hurdles of identifying ambulances amidst congested traffic settings, harnessing the power of cutting-edge object detection models using Deep learning, particularly YOLOv5 and YOLOv8[YOLO (You Only Look Once) is a family of object detection models that are based on convolutional neural networks (CNNs)]. By focusing on the intricate task of detecting ambulances in challenging urban scenarios, this study aims to provide a holistic insight and effective strategies for managing emergency situations with agility and efficacy in urban landscapes. The pursuit of robust detection capabilities, we employed YOLOv8, a cutting-edge object detection model known for its advanced performance in real-time applications. Our model, meticulously trained with a precision rate of 0.762, recall rate of 0.631, and mAP50 (mean Average Precision at IoU 0.50) of 0.69, demonstrates a high level of accuracy in identifying ambulances under challenging conditions. The achieved mAP50 of 0.69 signifies a robust average precision, especially at the commonly used IoU threshold of 0.50. This metric underscores the model's reliability in providing accurate predictions, contributing to the overall success of emergency vehicle detection in urban traffic environments.In addition to these training metrics, our model consistently demonstrates strong performance in practical applications, with output accuracies reaching 0.61 and 0.83. This further validates the model's efficacy in real-world scenarios, where the accuracy of emergency vehicle detection is pivotal for ensuring timely and precise emergency responses.This interdisciplinary approach leverages insights from both computer vision and transportation engineering domains to address the complex challenges associated with urban emergency response systems comprehensively.

Keywords- *Deep Learning, Convolutional Neural Networks, YOLOv8, precision rate, recall rate, mAP50, IoU threshold.*

INTRODUCTION

In the dynamic landscape of contemporary urban environments, the efficient detection of ambulances amidst heavy traffic congestion emerges as a critical challenge, carrying profound implications for public safety and emergency response systems. The escalating density of vehicles on roadways, coupled with the urgency of responding to emergencies, necessitates a sophisticated approach to ambulance detection that transcends conventional methods.

Emergency vehicles are crucial in situations threatening human life, but over 20% of Emergency Medical Services (EMS) patients face increased mortality due to traffic jams. The urgency to transport patients, especially those with life-threatening diseases, is often hindered by traffic bottlenecks, leading to delayed hospital arrivals. To address this issue, integrating an intelligent automated system with traffic management could prioritize emergency vehicles, alerting authorities or deploying road-clearing robots when necessary. Recognizing vehicles' emergency status is vital for efficient traffic clearance. The success of emergency vehicle response depends on swift navigation through crowds, a departure from traditional lights and sirens to attract attention.

Amidst this complex scenario, real-time object detection technologies play a pivotal role as transformative tools for enhancing public safety and streamlining emergency services. Picture a scenario where an ambulance urgently navigates through densely populated city streets during peak rush hours. In such situations, the ability to identify the ambulance’s presence swiftly and accurately amid the chaotic interplay of vehicles becomes paramount. Traditional manual methods of spotting emergency vehicles may lead to delays, potentially hindering the timely arrival of crucial medical assistance.

In contrast, real-time object detection technologies like YOLOv8 offer a proactive solution, enabling automated recognition of emergency vehicles such as ambulances with unparalleled speed and accuracy. By leveraging advanced algorithms and deep learning techniques, these systems can analyze live video feeds from traffic cameras or vehicle-mounted sensors, instantly flagging the presence of ambulances and alerting relevant authorities.

This seamless integration of technology into emergency response protocols not only expedites the arrival of medical aid but also minimizes the risk of accidents and ensures the safety of both patients and other road users. This research, in response to these challenges, delves into the integration of real-time object detection technologies as a transformative solution. Specifically, it explores the application of YOLO v5 and v8 models, equipped with advanced algorithms and trained on custom datasets, for the rapid and autonomous identification of ambulances in video streams or images.

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CHAPTER 2
LITERATURE SURVEY

In the realm of intelligent traffic management and emergency response systems, the detection of ambulances within congested traffic environments is of utmost importance. This literature survey aims to explore and synthesize existing research on ambulance detection in traffic scenarios [1], with a particular focus on methodologies utilizing YOLOv8 [2], an advanced object detection model.

The survey will commence by investigating cutting-edge techniques employed in ambulance detection, with an emphasis on YOLOv8 and its applications. Notable works in the field are expected to leverage YOLOv8's capabilities in real-time object detection, allowing for the discernment of the distinct visual characteristics of ambulances amidst complex urban traffic conditions.

Moreover, the literature survey will delve into key findings and outcomes from previous studies using YOLOv8. Insights into the accuracy, speed, and adaptability of YOLOv8-based ambulance detection models will be analysed [3]. The review will spotlight challenges encountered in ambulance detection, such as variations in lighting, diverse urban landscapes, and potential occlusions in traffic [4], specifically addressing how YOLOv8 copes with these challenges. The survey aims not only to summarize existing methodologies but also to identify gaps and limitations in the current literature, particularly within the context of YOLOv8.

This includes scenarios where YOLOv8-based approaches may fall short, such as under specific weather conditions or in the presence of heavily congested traffic [5]. Addressing these gaps will be crucial for proposing advancements in ambulance detection technology using YOLOv8 [6].This literature survey serves to offer a thorough examination of ambulance detection within traffic, with a particular focus on the efficacy of YOLOv8 [7].

By consolidating existing insights and identifying opportunities for enhancement within the YOLOv8 framework, the survey endeavors to establish a robust groundwork for the advancement of a sophisticated and efficient ambulance detection system [8], particularly in intricate traffic environments. Through this comprehensive analysis, the survey sets the stage for the development of innovative solutions aimed at improving emergency response and ensuring the safety of both emergency personnel and the public amidst challenging traffic conditions [9].

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CHAPTER 3

Deep Learning

Deep learning is a state-of-the-art machine learning method, which utilizes a complex network of artificial nodes with large amounts of hidden layers. Many of the techniques before the introduction of deep learning classify the task through semantic features information. Some examples of the semantic features are corners, edges, shapes, etc. A deep learning approach does not require the design of features ahead of time. These features are the results of optimum automatic learning. Therefore, this method is robust to various modes in the data as these features are not handcrafted. Some examples of the applications of deep learning approach are in object tracking, disease screening, physiotherapy, face retrieval, and remote sensing.

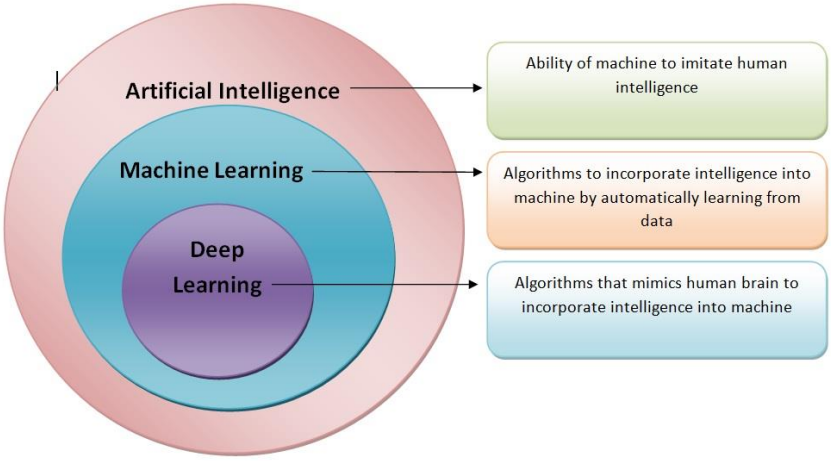

Fig 1:AI Vs ML Vs DL.

1. Automatic Feature Learning:

Deep learning models learn hierarchical representations of data, extracting abstract features through multiple layers. Lower layers detect simple features like edges, while higher layers learn complex features like object shapes. This automatic feature extraction eliminates the need for manual feature engineering, enhancing adaptability and performance across tasks.

2. Robustness to Data Variability:

Deep learning excels in handling diverse data distributions, adapting to variations and sources of variability. In disease screening, deep learning algorithms analyze medical images effectively despite differences in lighting and patient demographics. This robustness ensures reliable performance across different scenarios, enhancing the model's utility in real-world applications.

3. Applications of Deep Learning:

In object tracking, deep learning enables accurate detection and tracking of objects in videos for surveillance and navigation. Deep learning aids in disease screening by detecting abnormalities in medical images, assisting radiologists in early diagnosis. Applications in physiotherapy include analyzing physiological data to provide personalized exercise plans, enhancing patient outcomes and rehabilitation.

4. Advancements and Future Directions:

Ongoing research in deep learning focuses on architectural innovations and optimization techniques to improve model performance. With the rise of big data and hardware advancements, deep learning models are becoming more powerful and scalable. This ongoing progress enables breakthroughs in various domains, including healthcare, finance, agriculture, and autonomous systems.

3.1 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a class of deep neural networks primarily designed for processing structured grid data, such as images and videos. They have revolutionized various fields, including computer vision, image recognition, and natural language processing. Here's a detailed breakdown of CNNs:

1. **Architecture of CNNs:**

   Input layer:

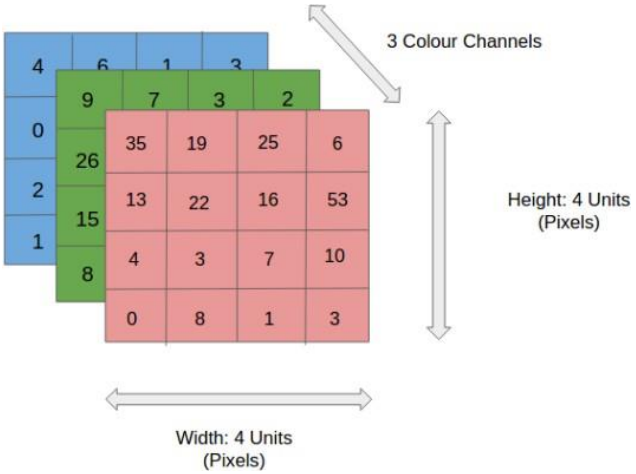

Fig 2:RGB Image

Convolutional Layers: These layers consist of filters (also called kernels) that slide over the input image to perform convolution operations. Convolution helps in capturing local patterns and features from the input data.

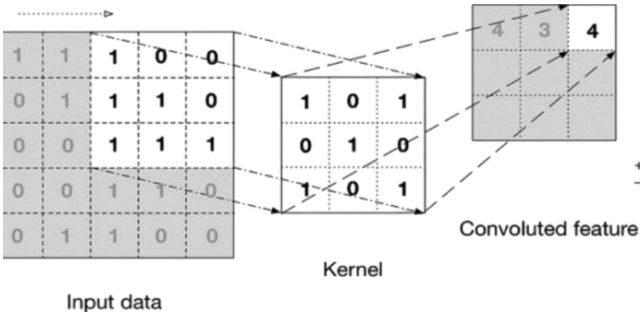

Fig 3: Convolution operation

Stride: It is the step size of the filter moving across the input data in convolutional neural networks. For example, a stride value of 1 would cause one pixel shift at a time thus altering the sizes of output feature maps. When strides are increased, then this results in smaller sized feature maps on output leading to spatial down- sampling and vice versa

Padding: Adding some border pixels before performing convolution operations on an input is called padding. At edges particularly, padding does maintain spatial dimensions and information. The aim here is for spatial dimensions as input so that no information is lost during convolution.

Activation Function: They are non-linear functions which enable complex patterns to be learnt by neural networks. Activation functions such as sigmoid, ReLU, tanh, softmax determine neuron activation which are crucial to approximating complex functions and changing inputs into them. ReLU has been preferred due to its simplicity and effectiveness for deep learning model

Pooling Layers: Pooling layers (commonly MaxPooling or AveragePooling) downsample the feature maps obtained from convolutional layers, reducing the spatial dimensions and computational complexity of the network while retaining important features.

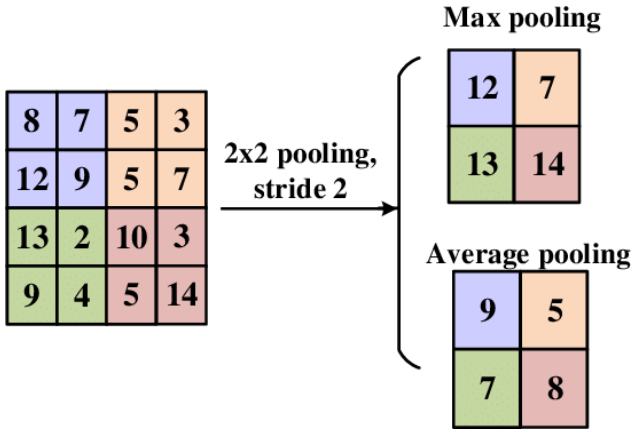

Fig 4: Pooling

Fully Connected Layers: After several convolutional and pooling layers, the extracted features are flattened and passed through one or more fully connected layers for classification or regression tasks.

2. Convolution Operation:

The convolution operation involves sliding a filter (kernel) over the input image and computing the element-wise multiplication between the filter and the overlapping region of the input.

By systematically applying the filter across the entire input image, convolutional layers extract features such as edges, textures, and shapes.

3. Pooling Operation:

Pooling layers reduce the spatial dimensions of the feature maps obtained from convolutional layers.

MaxPooling retains the maximum value within each pooling region, while AveragePooling computes the average value.

Pooling helps in achieving translation invariance and reducing the computational cost of the network.

4. Activation Functions:

Activation functions (e.g., ReLU, Sigmoid, Tanh) introduce non-linearity to the network, enabling it to learn complex patterns and relationships in the data. ReLU (Rectified Linear Unit) is commonly used in CNNs due to its simplicity and effectiveness in alleviating the vanishing gradient problem.

5. Training CNNs:

CNNs are trained using backpropagation and gradient descent algorithms. During training, the network learns to adjust its parameters (weights and biases) to minimize a loss function, typically associated with the difference between predicted and actual outputs. Common optimization algorithms used for training CNNs include Stochastic Gradient Descent (SGD), Adam, and RMSprop.

6. Applications of CNNs:

Image Classification: CNNs excel at tasks like classifying images into predefined categories, such as recognizing objects in photographs.

Object Detection: CNNs can detect and localize objects within images, enabling applications like autonomous vehicles, surveillance, and medical imaging.

Image Segmentation: CNNs can segment images into different regions or objects, facilitating tasks like medical image analysis and scene understanding.

Face Recognition: CNNs are widely used for face recognition tasks in security systems, social media platforms, and biometric authentication.

7. Transfer Learning:

Transfer learning involves leveraging pre-trained CNN models (such as VGG, ResNet, or Inception) trained on large datasets like ImageNet. By fine-tuning these pre-trained models on domain-specific data, practitioners can achieve excellent performance with limited data and computational resources. CNNs have significantly advanced the state-of-the-art in various domains, demonstrating remarkable capabilities in understanding and processing complex visual data. Their versatility, combined with advancements in hardware and algorithms, continues to drive innovation in deep learning and computer vision.

3.2 Introduction to YOLO versions

YOLO version 1:

Redmon et al. developed the YOLO (You Only Look Once) object detection network as an efficient alternative to reduce the runtime complexities associated with R-CNN and its variants. Unlike R-CNN, YOLO doesn't rely on regional proposals for object localization and classification. Instead, it divides the entire image into an SxS grid and places 'm' bounding boxes within each grid. Each bounding box predicts class probabilities and offset values. To streamline predictions, boxes with class probabilities below a specified threshold are suppressed, eliminating the need for extensive region proposal computations. This design choice significantly accelerates object detection processes compared to the traditional R-CNN methods. Representation of steps of object detection using YOLO Version 1 is **fig 5**

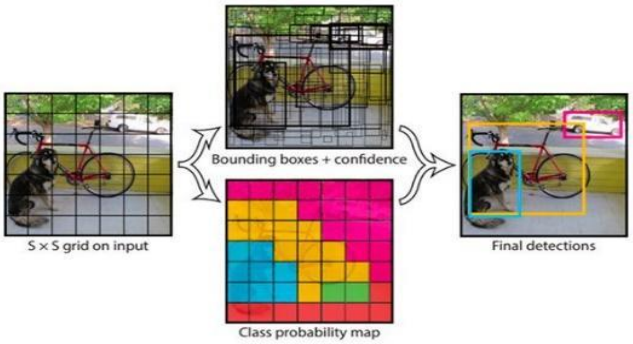

Fig 5: Steps of object detection using YOLO Version 1.

YOLO version 2:

In YOLO version 1, notable architectural enhancements include the introduction of Batch Normalization to improve detector performance and prevent overfitting without relying on dropout layers. YOLO version 2 addresses the efficiency decrease during testing caused by a sudden image resolution increase by fine-tuning on 448x448 images for 10 epochs, gradually adapting to high resolutions.

The model in YOLO version 2 eliminates fully connected layers, predicting objectness scores with anchor boxes, improving recall at the cost of mAP. Training improvements involve using bounding boxes generated with the Bag-of-F k-means algorithm and a defined distance metric. Additionally,

YOLO version 2 stabilizes the model by constraining bounding box coordinates with logistic activation, ensuring values stay within [0,1].

YOLO version 3:

YOLO version 3, an enhancement by Redmon et al, adopts a distinct approach from YOLO version 2. It replaces the SoftMax classifier with independent logistic classifiers for each class, facilitating more efficient handling of multi-class predictions. In contrast to YOLO version 2's use of Darknet-19, version 3 employs a hybrid feature extraction approach, combining features from Darknet-19 and a residual network. However, the proposed architecture introduces shortcut connections, enhancing efficiency for detecting small objects but potentially diminishing performance for larger and medium-sized objects.

YOLO version 4:

Derived from Bag-of-Freebies and Bag-of-Specials methods, YOLO version 4 optimizes accuracy by balancing inference time and training costs. Inspired by genetic algorithms, it selects optimal hyperparameter values for improved performance. Introducing data augmentation techniques such as Self-Adversarial Training (SAT) and Mosaic enhances the model's adaptability. Additionally, YOLO version 4 incorporates modifications like Cross Mini-Batch Normalization and Spatial Attention Module to further refine object detection capabilities. YOLO version 4 integrates advanced post-processing techniques like Non-Maximum Suppression (NMS) and Soft-NMS, ensuring accurate localization and classification of objects even in cluttered scenes.

YOLO version 5:

In a departure from previous versions developed using the Darknet research framework, YOLO version 5 marks a significant shift by being the first version developed in the PyTorch framework. This transition enhances YOLO version 5's production readiness as PyTorch offers greater configurability compared to Darknet. Notably, this version showcases improved runtime efficiency, with YOLO version 5 demonstrating a faster inference time of 140 frames per second, a notable advancement compared to its predecessor, YOLO version 4, which achieves 50 frames per second using the same PyTorch library. Representation of steps of object detection using YOLO Version 1 is **fig.6**

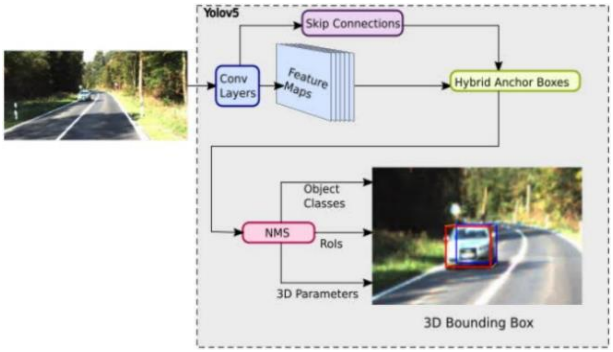

Fig 6: Steps of object detection using YOLO Version 5.

YOLO version 6:

YOLOv6 is a leading-edge object detection model known for its speed and accuracy in real-time applications. It builds upon the success of the YOLO series, focusing on efficiency and performance enhancements. With advanced architecture and training techniques, YOLOv6 delivers superior object detection results. Offering customizable pre-trained models, YOLOv6 excels in high-precision detection with rapid inference speeds. Widely applied in computer vision fields like surveillance and autonomous driving, YOLOv6 stands out for its robust and efficient object detection capabilities.

YOLO version 7:

YOLOv7 algorithms are highly proficient in recognizing and tracking objects within production lines, thus optimizing efficiency in manufacturing processes. This capability enables real-time monitoring as objects traverse various stages of production, facilitating seamless workflow management. Moreover, YOLOv7's advanced object detection capabilities play a crucial role in quality control by swiftly identifying defects during manufacturing processes. By offering dual functionality for both object tracking and defect detection, YOLOv7 significantly enhances precision and quality assurance in manufacturing operations. Its deployment streamlines production activities, leading to more efficient and accurate outcomes across the manufacturing environment.

YOLO version 8:

YOLOv8 stands as a cutting-edge deep learning model, renowned for real-time object detection in computer vision applications. Leveraging advanced architecture and algorithms, YOLOv8 excels in achieving both precision and efficiency in identifying objects. Its state-of-the-art capabilities have positioned it as a pivotal tool in various industries, including robotics, autonomous driving, and video surveillance. This model's versatility makes it adaptable to diverse scenarios, ensuring optimal performance in dynamic and real-world environments. YOLOv8's widespread adoption underscores its significance as a leading solution for rapid and accurate object detection, contributing significantly to advancements in computer vision technology. Representation of steps of object detection using YOLO Version 8 is **fig.7**

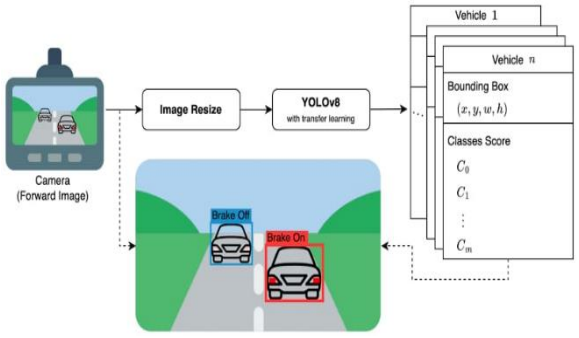

Fig 7: Steps of object detection using YOLO Version 8

3.2 RECURRENT NEURAL NETWORKS (RNNs) for audio recognition:

3.2.1 Introduction to Recurrent Neural Networks (RNNs):

Recurrent Neural Networks (RNNs) are a class of artificial neural networks designed for processing sequential data by maintaining an internal state. Unlike traditional feedforward neural networks, RNNs have connections that form directed cycles, allowing them to exhibit dynamic temporal behavior.

3.2.2 Architecture of Recurrent Neural Networks:

RNNs consist of recurrent connections that enable them to capture temporal dependencies in sequential data. Each time step in the input sequence corresponds to one step in the RNN computation. At each time step, the RNN takes an input vector and produces an output vector, while also maintaining a hidden state vector that captures information about the past sequence.

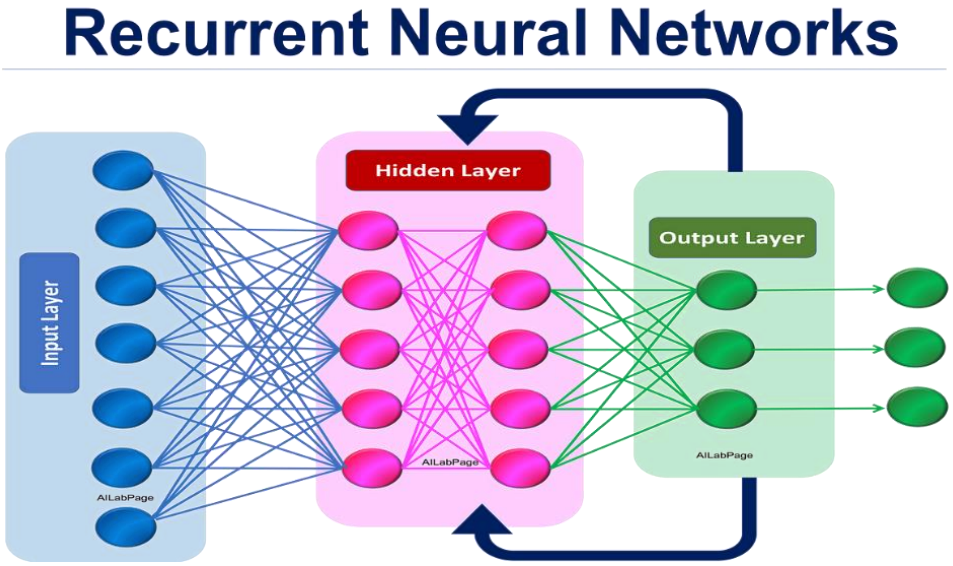

Fig 8: Architecture of Recurrent Neural Networks

3.2.3 Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs):

Traditional RNNs suffer from the vanishing gradient problem, limiting their ability to capture long-term dependencies. LSTM and GRU units are specialized variants of RNNs designed to address this issue. LSTM units incorporate memory cells and gating mechanisms to selectively retain or discard information over time, making them more effective for learning long-range dependencies. GRU units, a simplified version of LSTMs, also employ gating mechanisms but with fewer parameters, making them computationally more efficient.

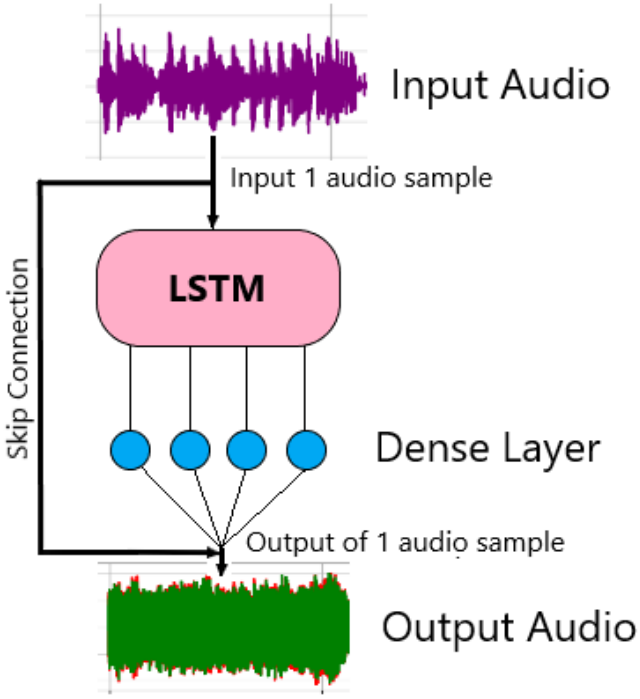

Fig 9: Deep Learning-LSTM

3.2.4 Feature Extraction for Audio Recognition:

Audio data is typically preprocessed and transformed into a suitable feature representation before being fed into the RNN. Common feature representations include Mel-Frequency Cepstral Coefficients (MFCCs), spectrograms, or raw waveform samples. These features capture important characteristics of the audio signal relevant to the recognition task.

3.2.5 Model Architecture for Audio Recognition:

RNN architectures for audio recognition often consist of multiple recurrent layers (LSTM or GRU) followed by one or more fully connected layers for classification. The recurrent layers process the sequential input data, capturing temporal dependencies, while the fully connected layers perform high-level feature extraction and classification.

3.2.6 Training RNNs for Audio Recognition:

RNNs are trained using supervised learning techniques. A dataset containing labeled audio samples is used for training, with the network learning to map input audio sequences to their corresponding labels. Training involves adjusting the network parameters (weights and biases) using optimization algorithms such as backpropagation through time (BPTT) and gradient descent.

3.2.7 Evaluation of RNNs for Audio Recognition:

The performance of the trained RNN model is evaluated using a separate test dataset. Common evaluation metrics include accuracy, precision, recall, and F1 score, assessing the model's ability to correctly classify audio samples.

3.2.8 Applications of RNNs in Audio Recognition:

RNNs have various applications in audio recognition, including:

Speech recognition: Converting spoken language into text.

Speaker identification: Recognizing the identity of a speaker from their voice.

Music classification: Classifying music tracks into genres or identifying musical instruments.

Environmental sound classification: Identifying sounds in the environment, such as sirens, f footsteps, or birdcalls.

In summary, Recurrent Neural Networks, particularly LSTM and GRU variants, are effective for audio recognition tasks due to their ability to capture temporal dependencies in sequential data. Preprocessing audio data into suitable feature representations and designing appropriate model architectures are crucial steps in leveraging RNNs for audio recognition applications.

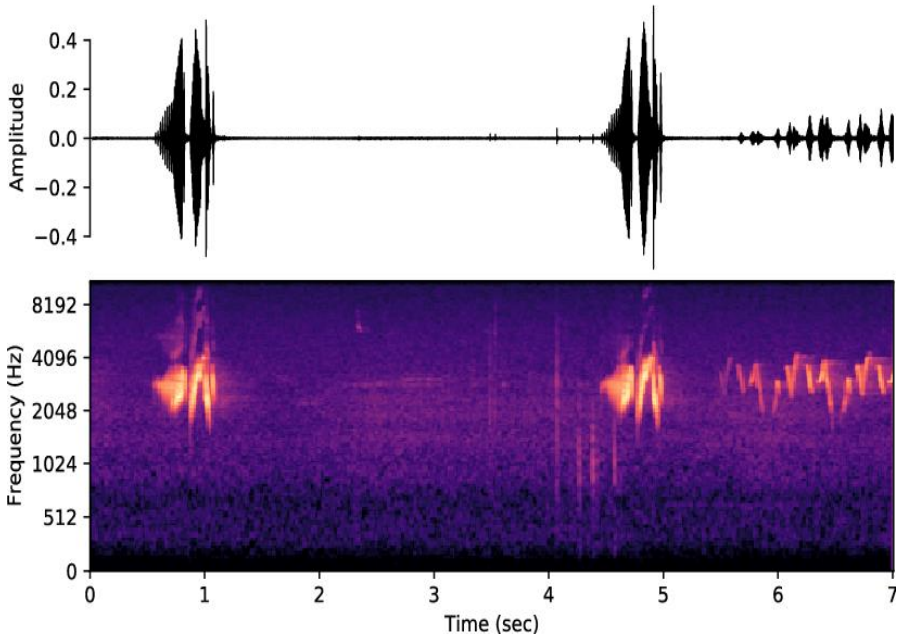

Fig 10 : LSTM Application of Audio Signal

3.3 Google Firebase

Google Firebase is a comprehensive platform designed to streamline the development process of mobile and web applications. It offers a wide range of tools and services that cater to various aspects of app development, analytics, testing, and user engagement. Firebase has garnered significant popularity among developers worldwide due to its versatility, scalability, and ease of integration.

Main Features of Firebase:

1.Real-time NoSQL Database: Firebase provides a real-time NoSQL database that enables developers to store and synchronize data across multiple clients in real time. This feature is particularly beneficial for building collaborative applications and ensuring data consistency across different devices and platforms.

2. Authentication Services: Firebase offers robust authentication services supporting various authentication methods such as email/password, phone number, and social media logins. This simplifies the process of adding user authentication to applications, ensuring secure access for users.

3. Cloud Firestore: Firestore is Firebase's scalable NoSQL cloud database, offering enhanced data storage and synchronization capabilities. With support for seamless data syncing and offline access, Firestore enables developers to build responsive and reliable apps that work seamlessly across different devices and platforms.

4. Cloud Functions: Firebase allows developers to extend their app's functionality with serverless cloud functions. These functions run in response to events triggered by Firebase features or HTTPS requests, enabling developers to perform backend tasks without managing servers.

5. Cloud Storage: Firebase offers cloud storage solutions for storing user-generated content such as images, videos, and files. With scalable storage options and built-in security features, Firebase Cloud Storage simplifies file storage and retrieval for apps.

6. Cloud Messaging: Firebase Cloud Messaging (FCM) enables developers to send push notifications and messages to users across platforms, including Android, iOS, and web. With FCM, developers can engage users, re-engage inactive users, and drive app growth.

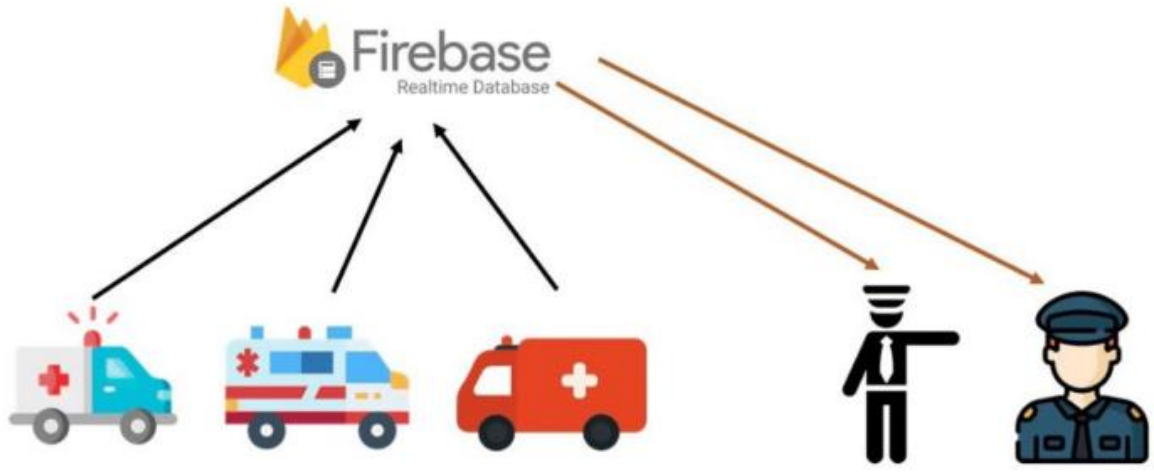

Fig 11: Interfacing with Google Firebase

Applications of Firebase:

1. Real-time Collaboration Apps: Firebase's real-time database and synchronization capabilities make it ideal for building collaborative applications such as messaging apps, collaborative document editors, and multiplayer games. These apps rely on instant updates and data consistency across multiple users.

2 . Social Media Authentication: Many apps leverage Firebase's authentication services to enable seamless login and registration using social media accounts such as Google, Facebook, and Twitter. This simplifies the onboarding process for users and enhances app security.

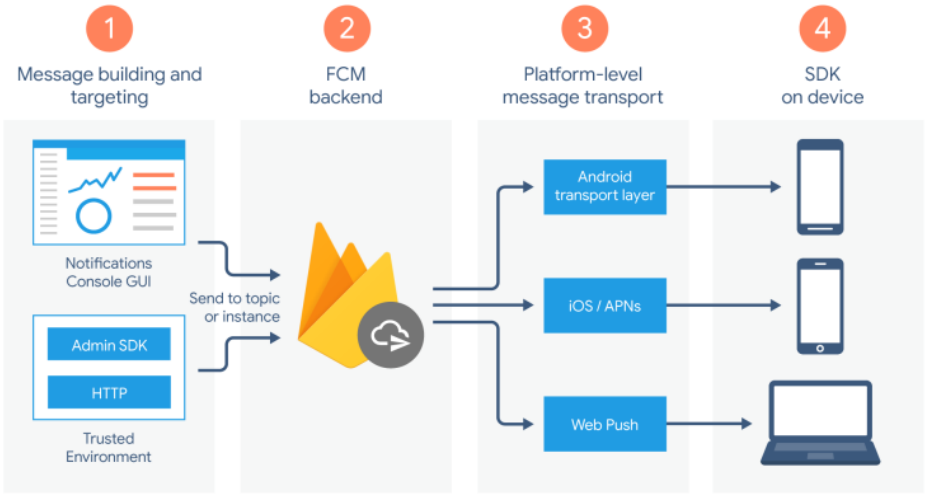

Fig 12: Social Media Authentication

3. Content Sharing Apps: Firebase Cloud Storage enables developers to build content sharing apps where users can upload, store, and share photos, videos, and files securely. These apps often include features like user-generated content moderation, file versioning, and access controls.

4. Real-time Dashboards and Analytics: Firebase's analytics and performance monitoring tools are utilized to build real-time dashboards and reporting systems for tracking app usage, user engagement, and revenue metrics. These insights help businesses make data-driven decisions and optimize their apps for better performance.

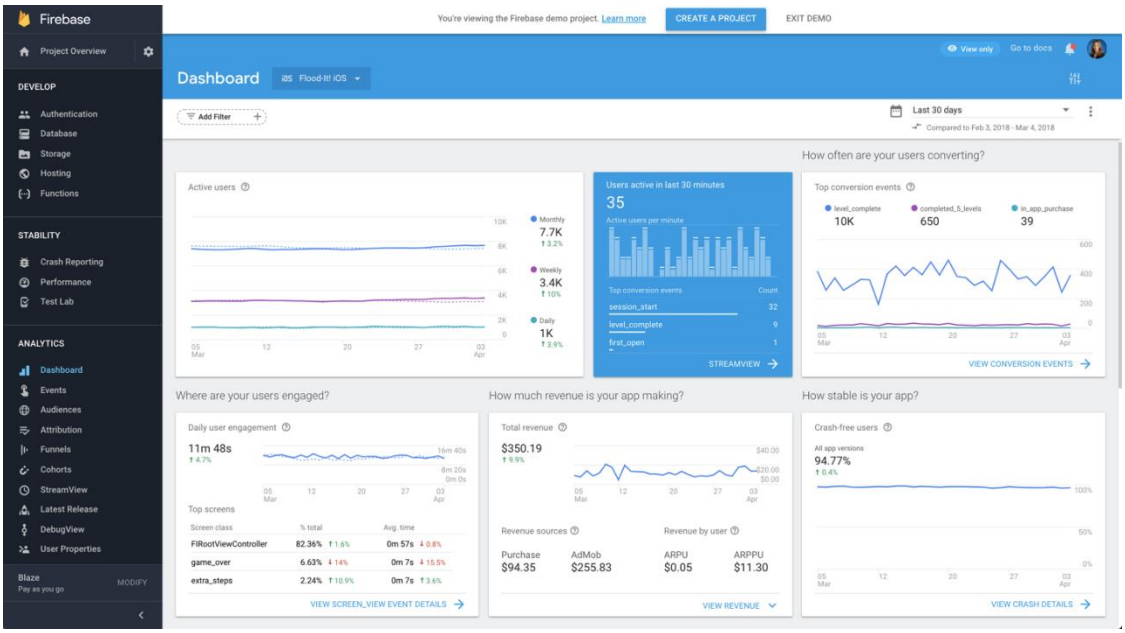

Fig 13: Real-time Firebase Dashboards and Analytics

CHAPTER 4

RESEARCH METHOD

4.1 AMBULANCE IDENTIFICATION THROUGH IMAGE DETECTION

4.1.1 Efficient feature representation:

Depth wise Convolution: By processing each channel of the input feature map separately, depth wise convolution efficiently captures spatial features relevant to ambulance detection. This approach reduces redundancy and improves computational efficiency.

Pointwise Convolution: Following depth wise convolution, pointwise convolution adjusts the depth based on the number of input channels, allowing for dimensionality reduction without sacrificing representational power. This step is crucial for maintaining accuracy while reducing the model's computational complexity.

4.1.2 Mobile-Friendly Architecture:

YOLOv5 and V8 models are specifically designed for mobile applications, where computational resources are limited compared to desktop environments. By leveraging depth wise and pointwise convolutions, these models achieve a balance between accuracy and efficiency, making them well-suited for deployment on resource-constrained devices such as smartphones and tablets. The streamlined architecture of YOLOv5 and V8 models, inspired by MobileNet V2, ensures that they can operate efficiently on mobile hardware without compromising performance.

4.1.3 Real-Time Inference:

The efficient design of YOLOv5 and V8 models enables real-time inference, allowing for rapid detection of ambulances in video streams or live camera feeds. This capability is essential for applications requiring timely response to emergency situations. By minimizing computational overhead through depth wise and pointwise convolutions, these models can process frames quickly, making them suitable for dynamic environments where ambulances may be moving rapidly or obscured by other objects.

4.2 AMBULANCE IDENTIFICATION THROUGH SIREN DETECTION

4.2.1 Efficient Feature Representation:

4.2.1.1 Styles

For audio detection, efficient feature representation involves extracting relevant characteristics from audio signals while minimizing redundancy and computational overhead.

4.2.1.2 Spectrogram Representation:
Spectrograms are a common feature representation for audio signals. They capture the frequency content of the audio signal over time, providing valuable information about its spectral characteristics.

4.2.1.3 Mel-Frequency Cepstral Coefficients (MFCCs):
MFCCs are another widely used feature representation for audio signals. They capture the spectral envelope of the audio signal and are particularly effective for tasks such as speech recognition and environmental sound classification.

4.2.2 Mobile-Friendly Architecture:

4.2.2.1 Lightweight Models:
Like YOLOv5 and V8 models designed for mobile applications in image detection, lightweight models tailored for audio detection are essential for deployment on resource-constrained devices.

4.2.2.2 Efficient Convolutional Layers:
Utilizing depth wise and pointwise convolutions in neural network architectures for audio detection can help achieve a balance between accuracy and efficiency, making the models suitable for deployment on mobile devices.

4.2.3 Real-Time Inference:

4.2.3.1 Low Latency Processing:
Efficient design principles, such as those seen in YOLOv5 and V8 models for image detection, can be applied to audio detection models to enable real-time inference. This is crucial for applications requiring timely detection of audio events, such as identifying emergency sirens or alarms in live audio streams.

4.2.3.2 Streamlined Architectures:
Inspired by MobileNet V2, streamlined architectures for audio detection models can ensure efficient operation on mobile hardware without compromising performance. These models can process audio streams rapidly, making them suitable for dynamic environments where audio events may occur quickly.

Efficient feature representation, lightweight architectures, and real-time inference capabilities are crucial for audio detection on resource-constrained devices. Utilizing techniques such as spectrograms or MFCCs for feature extraction, designing lightweight neural network architectures with efficient convolutional layers, and optimizing models for low latency processing can enable real-time detection of audio events in various applications, including emergency sound detection and environmental monitoring

CHAPTER -5 : METHODOLOGY

5.1 METHODOLOGY FOR IMAGE DETECTION

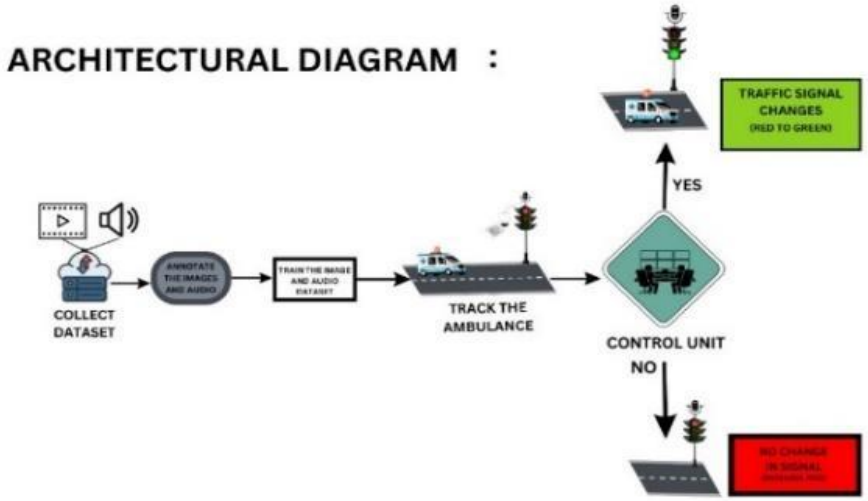

Fig 14: Architectural diagram for Methodology

5.1.1 Dataset Acquisition:

In the dataset acquisition process, it's imperative to emphasize the diversity and representativeness of the collected data. In addition to urban landscapes, data acquisition efforts should encompass suburban and rural environments to capture a comprehensive range of traffic scenarios. Moreover, collaboration with local emergency services and traffic management authorities can facilitate access to real-time data streams, enriching the dataset with dynamic traffic patterns and emergency response scenarios. Incorporating data from multiple sources, including surveillance cameras, drones, and vehicle-mounted sensors, enhances the dataset's richness and variability, crucial for training robust detection models.

To augment the dataset further, novel techniques such as synthetic data generation and domain adaptation can be employed. Synthetic data generation involves creating realistic yet artificial images or videos using computer graphics techniques, thereby diversifying the dataset and simulating scenarios that may be challenging to capture in real-world settings. Domain adaptation techniques focus on transferring knowledge from a source domain, where labeled data is abundant, to a target domain, where labeled data may be scarce or unavailable. By aligning feature distributions between the source and target domains, domain adaptation facilitates the effective utilization of labeled data from related but distinct environments, enhancing model generalization and performance in target domains.

5.1.2 Pre-processing:

In the pre-processing phase, advanced techniques such as data augmentation, domain-specific normalization, and semantic segmentation play a pivotal role in preparing the dataset for model training.

While traditional data augmentation techniques such as random rotations, translations, and scaling enhance the dataset's variability, domain-specific normalization techniques adapt the data distribution to the target domain, improving model performance and convergence. Semantic segmentation, a pixel-level classification technique, provides detailed annotations of objects within the scene, facilitating

precise localization and classification of ambulances amidst complex traffic environments.

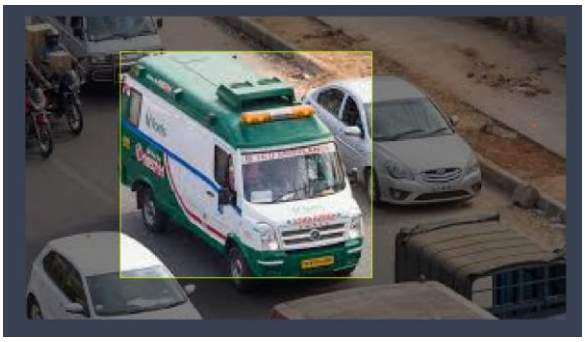

Fig 15: Example of manual annotation of an ambulance image (Box labelling or tagging).

In addition to traditional pre-processing techniques, attention should be given to addressing class imbalance and data scarcity issues, which are common challenges in object detection tasks. Techniques such as oversampling minority classes, generating synthetic samples, and utilizing transfer learning from related tasks can mitigate these issues, ensuring adequate representation of ambulance instances in the training dataset. Furthermore, data quality control measures, including manual inspection and annotation verification, are essential for ensuring the accuracy and reliability of the training data, minimizing annotation errors and inconsistencies that may impact model performance.

These resized pictures went through augmentation techniques including rotation, flipping, zooming and other transformations that increased diversity of the dataset thus improving generalization capability of the model.

This meticulous calibration between image sizes and requirements of pretrained models ensured compatibility as well as optimized performance of the model during subsequent training and evaluation steps. In addition, data augmentation was approached systematically so that it would be easily integrated into pre-trained models and entail robustness of developed –recognition system.

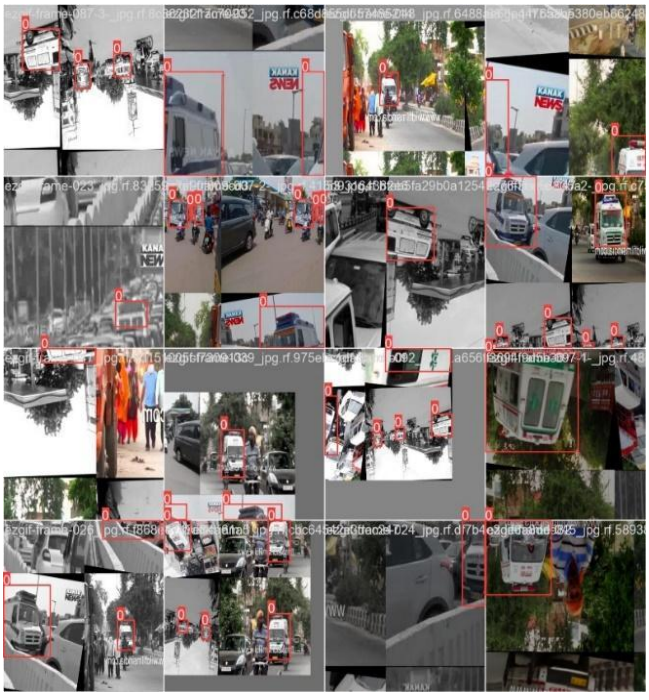

Fig 16: Set of Ambulance images including rotation, flipping, zooming and other transformations.

5.1.3 Dataset Partition:

This project categorized the dataset into two major subdivisions namely: train dataset and test dataset in a 70-30% balance ratio. This is a conscious effort to ensure that the majority (70%) of data is used to determine the model while 30% is left to measure how the model would perform on unseen data.

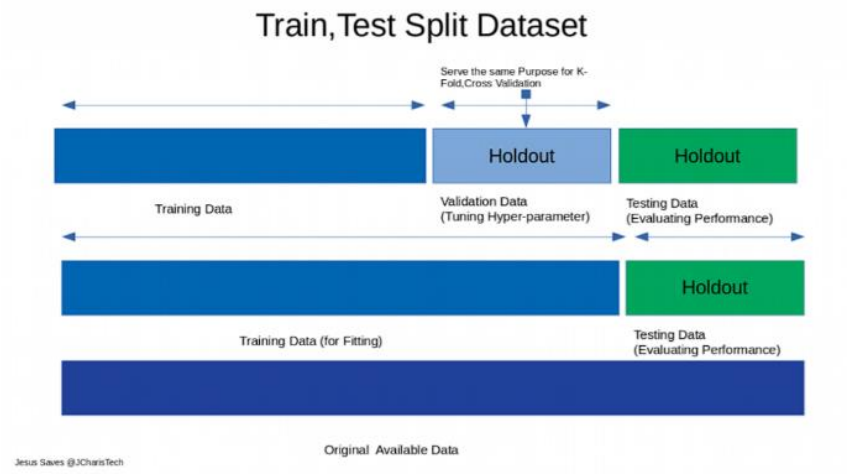

Fig 17: Splitting of Data(images)

5.1.4 Algorithm Selection and Training:

Once the dataset is prepared, the selected algorithm (YOLOv5 or YOLOv8) is trained using the annotated images. During training, the algorithm learns to detect ambulances by adjusting its internal parameters based on the provided training data. This process involves feeding batches of images into the algorithm, calculating the loss function to measure the difference between predicted and ground-truth bounding boxes, and updating the model's weights through backpropagation to minimize this loss. The selection of the YOLOv5 and YOLOv8 models for ambulance detection is informed by their state-of-the-art performance in real-time object detection tasks. However, the training process extends beyond model selection to encompass hyperparameter optimization, regularization techniques, and curriculum learning strategies.

Hyperparameter tuning, facilitated by techniques such as grid search, random search, or Bayesian optimization, aims to find the optimal configuration of model parameters, including learning rates, batch sizes, and regularization coefficients, to maximize detection performance while mitigating overfitting.

Regularization techniques, such as dropout, weight decay, and batch normalization, are employed to prevent model overfitting and improve generalization to unseen data. Curriculum learning, inspired by human learning strategies, involves progressively introducing training samples based on their complexity, starting with simple scenarios, and gradually increasing the difficulty level, thereby enhancing the model's robustness and adaptability to diverse traffic conditions. Moreover, the training process should prioritize efficiency and scalability to accommodate large-scale datasets and complex model architectures. Techniques such as distributed training, model parallelism, and hardware acceleration (e.g., GPUs, TPUs) can accelerate the training process and enable the exploration of larger model architectures and datasets. Additionally, transfer learning from pre-trained models on related

tasks (e.g., object detection in natural scenes) can bootstrap model training and improve convergence, especially when labeled ambulance data is limited.
By leveraging pre-trained features and fine-tuning them on the target task, transfer learning enables the efficient utilization of domain-specific knowledge, enhancing model performance and reducing the need for large, annotated datasets.

```
      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      32/35      6.44G      1.336      1.011      1.579          6        800: 100% 111/111 [00:59<00:00,  1.85it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 6/6 [00:02<00:00,  2.11it/s]
                   all        168        254      0.747      0.622      0.675      0.358

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      33/35      6.46G      1.304     0.9848      1.559          5        800: 100% 111/111 [00:55<00:00,  2.01it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 6/6 [00:03<00:00,  1.58it/s]
                   all        168        254      0.773      0.604      0.682      0.362

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      34/35      6.46G      1.271     0.9513      1.528          5        800: 100% 111/111 [00:55<00:00,  2.01it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 6/6 [00:02<00:00,  2.08it/s]
                   all        168        254      0.766      0.617      0.684      0.357

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      35/35      6.45G       1.26     0.9268      1.523          4        800: 100% 111/111 [00:55<00:00,  2.00it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 6/6 [00:02<00:00,  2.08it/s]
                   all        168        254      0.759      0.634      0.697      0.366

35 epochs completed in 0.602 hours.
Optimizer stripped from runs/detect/train/weights/last.pt, 22.5MB
Optimizer stripped from runs/detect/train/weights/best.pt, 22.5MB

Validating runs/detect/train/weights/best.pt...
Ultralytics YOLOv8.0.196 🚀 Python-3.10.12 torch-2.1.0+cu121 CUDA:0 (Tesla T4, 15102MiB)
Model summary (fused): 168 layers, 11125971 parameters, 0 gradients, 28.4 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 6/6 [00:07<00:00,  1.20s/it]
                   all        168        254      0.721       0.63      0.688      0.368
```

Fig 18: Training Progression across Epochs

5.1.5 Model Creation:

The process of model creation extends beyond architectural selection to encompass feature engineering, transfer learning, and ensemble methods. Feature engineering involves extracting relevant features from raw data to facilitate effective model training and inference. In the context of ambulance detection, features such as vehicle size, shape, color, and motion characteristics can be extracted and fed into the detection model to improve accuracy and robustness. Transfer learning, leveraging pre-trained models on large-scale datasets such as CO or ImageNet, accelerates the training process and improves detection performance, especially when annotated ambulance data is limited. Ensemble methods, such as model averaging, boosting, or stacking, combine the predictions of multiple base models to produce a more accurate and reliable detection outcome, leveraging the diversity of individual models and reducing the risk of overfitting.
Additionally, attention should be given to model interpretability and explainability, especially in safety-critical applications such as ambulance detection. Techniques such as attention mechanisms, saliency maps, and gradient-based attribution methods can elucidate the model's decision-making process and highlight regions of interest within the input data, providing valuable insights into the factors influencing detection outcomes.

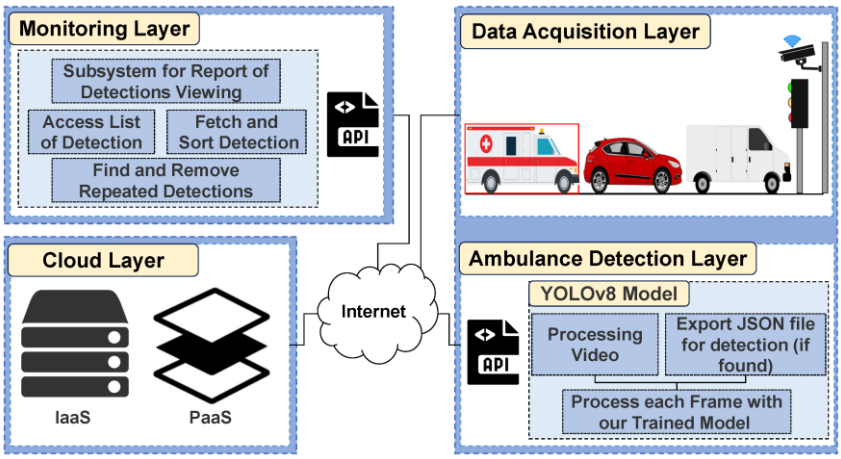

Fig 19: Evaluating of another dataset on the trained model.

5.1.6 Evaluation:

The evaluation phase of machine learning models constitutes a critical stage in assessing their efficacy and robustness. This phase involves subjecting the trained models to rigorous testing using unseen data to gauge their performance and generalization capabilities. While traditional metrics like precision, recall, and F1 score offer fundamental insights, incorporating advanced evaluation measures such as mean Average Precision (mAP), Intersection over Union (IoU), and receiver operating characteristic (ROC) curves enhances the understanding of model behavior across various operating conditions and detection thresholds. Mean Average Precision (mAP) serves as a comprehensive metric, particularly in object detection tasks, by considering precision-recall trade-offs across all classes. Intersection over Union (IoU) evaluates the spatial overlap between predicted and ground truth bounding boxes, offering a nuanced perspective on localization accuracy. ROC curves provide insights into the trade-offs between true positive and false positive rates across different classification thresholds, aiding in model optimization.

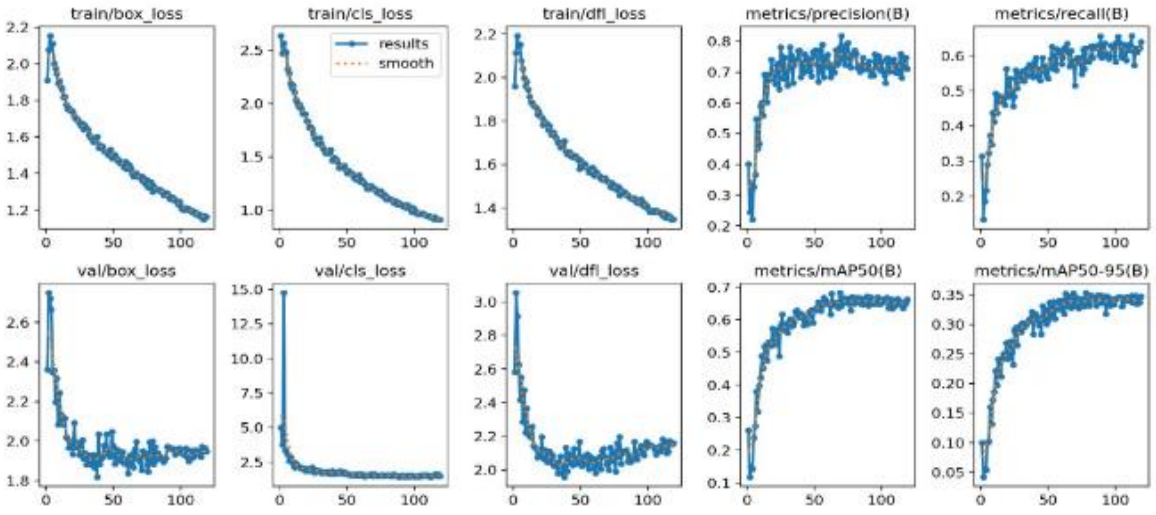

Fig 20 Performance metrics

5.1.7 Validation:

The validation phase of machine learning models represents a crucial step in ensuring their reliability and effectiveness. This phase involves subjecting the trained models to thorough validation using independent datasets to assess their performance and generalization capabilities in real-world scenarios. While traditional metrics like accuracy, precision, and recall provide fundamental insights, incorporating advanced validation measures such as cross-validation, confusion matrices, and calibration plots enhances the understanding of model behaviour across diverse datasets and conditions. Cross-validation techniques, such as k-fold cross-validation, help assess the stability and robustness of the model by partitioning the dataset into multiple subsets for training and validation.

This approach provides valuable insights into the model's consistency and potential overfitting or underfitting issues.

Confusion matrices offer a comprehensive visualization of the model's performance by summarizing the predicted versus actual class labels. They enable the analysis of true positive, true negative, false positive, and false negative predictions, facilitating a detailed assessment of classification accuracy and error patterns.

Calibration plots provide a graphical representation of the model's predicted probabilities against the observed outcomes. They help evaluate the calibration of the model's confidence scores, revealing any discrepancies between predicted probabilities and actual probabilities of class membership.

After subjecting the trained model to thorough validation using a diverse set of real-world videos depicting various traffic scenarios, lighting conditions, and dynamic environments, the model has demonstrated remarkable accuracy and precision in its predictions.

The results are very clear in **fig21**, **fig22** which are from the video inputs. The validation results confirm the model's exceptional performance across different contexts, highlighting its robustness and reliability in identifying ambulances under challenging conditions.

In particular, the model showcases its ability to accurately detect ambulances amidst congested traffic, adverse lighting conditions, and rapidly changing scenes. Regardless of the complexity of the environment, the model consistently delivers precise predictions, showcasing its adaptability and effectiveness in real-world settings.

These validation results serve as a testament to the model's efficacy and reliability, reinforcing its suitability for deployment in ambulance detection systems aimed at enhancing public safety and emergency responsiveness. The model's outstanding performance across a wide range of scenarios underscores its potential to make a significant impact in improving emergency services and saving lives.

Fig.21

Fig.22

5.2 METHODOLOGY FOR SIREN DETECTION

5.2.1 Dataset Acquisition:

1.Diversity in Data Collection:

Siren audio detection demands a diverse dataset reflecting various environments where sirens are encountered. This diversity ensures that the model is trained to recognize sirens accurately across different settings, including urban, suburban, and rural areas. The dataset should cover a range of emergency scenarios to capture the variability in siren sounds under different circumstances, such as ambulance sirens in traffic, fire truck sirens in residential areas, or police sirens during pursuits.

2.Collaboration with Authorities:

Partnering with local emergency services and traffic management authorities provides access to real-time siren audio streams, enriching the dataset with authentic emergency response scenarios and traffic patterns. This collaboration enables the collection of high-quality, labeled data, which is essential for training robust siren detection models capable of accurately identifying sirens amidst background noise and environmental factors.

3.Multi-Source Data Integration:

Integrating data from diverse sources such as surveillance microphones, emergency vehicle recordings, and environmental sound sensors enhances the richness and variability of the dataset. By incorporating audio samples captured from different devices and locations, the model becomes more adept at recognizing sirens in various acoustic environments, contributing to its overall performance and generalization ability.

4.Novel Data Augmentation Techniques:
To further enhance the dataset, novel data augmentation techniques like synthetic data generation and domain adaptation can be employed. Synthetic data generation involves creating artificial audio samples that simulate emergency scenarios, augmenting the dataset with additional instances and variations of siren sounds. Domain adaptation techniques help improve the model's performance by transferring knowledge from related but distinct audio environments, ensuring that the model can generalize effectively to unseen data.

Important Features and Considerations:

1.Label Quality: Ensuring accurate and consistent labeling of siren audio samples is paramount to the success of the dataset acquisition process. Clear labeling facilitates effective model training and evaluation.
2.Balanced Representation: Striving for a balanced representation of different types of sirens (e.g., ambulance, fire truck, police) and background noise conditions helps prevent bias in the model and ensures robust performance across all scenarios.
3.Data Preprocessing: Proper preprocessing techniques such as noise reduction, normalization, and feature extraction are essential for preparing the dataset for model training. Clean, standardized data enhances the model's ability to learn meaningful patterns and features.
4.Ethical Considerations: Respecting privacy and ethical considerations in data collection, especially when collaborating with authorities and collecting real-time audio streams, is crucial. Clear consent and anonymization protocols should be established to protect individuals' privacy rights.
5.Continuous Improvement: Dataset acquisition is an iterative process that may require ongoing refinement and augmentation as the model evolves. Regular evaluation and feedback loops help identify areas for improvement and ensure the dataset remains relevant and effective for model training.

5.2.2 Pre-processing:

Convert Raw Audio Files:
Convert raw audio recordings of ambulance sirens into a suitable format like WAV or FLAC. This conversion ensures compatibility with audio processing libraries and simplifies feature extraction.

Data Augmentation:
In the pre-processing phase, data augmentation techniques specific to audio signals can be applied to increase dataset variability. Techniques such as pitch shifting, time stretching, and adding background noise can simulate different acoustic conditions, enhancing the model's robustness to various environmental factors.

```
In [3]:
### siren_1
plt.figure(figsize=(14,5))
data,sample_rate=librosa.load(filename)
librosa.display.waveshow(data,sr=sample_rate)
plt.title('Waveform')
plt.xlabel('Time (s)')
plt.ylabel('Amplitude')
plt.tight_layout()
ipd.Audio(filename)
```

Out[3]: 0:00 / 0:00

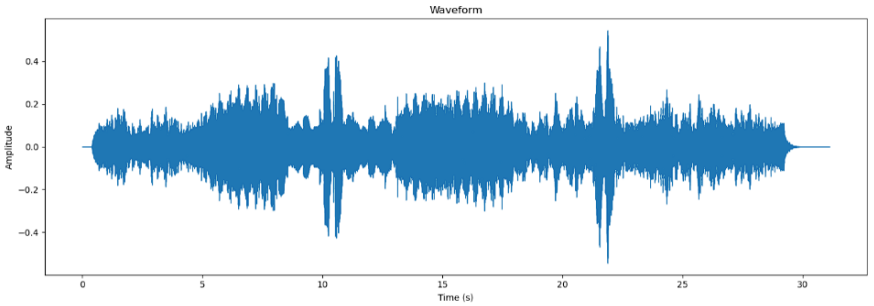

Fig 23: Audio Waveform Representation

```
# Original audio with 2 channels
plt.figure(figsize=(12, 4))
plt.title('Waveform')
plt.xlabel('Time (s)')
plt.ylabel('Amplitude')
plt.plot(wave_audio)
```

```
]: [<matplotlib.lines.Line2D at 0x207bffe6b00>,
    <matplotlib.lines.Line2D at 0x207ba010040>]
```

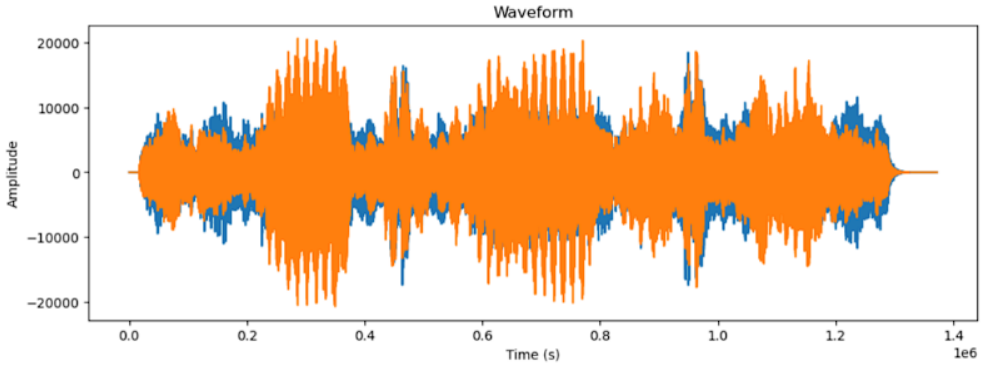

Fig 24: Audio Waveform with Noise Representation

Feature Extraction:

Feature extraction in the context of deep learning refers to the process of automatically extracting meaningful and informative representations or features from raw data. In deep learning, feature extraction is often performed using deep neural networks, which learn hierarchical representations of data through multiple layers of interconnected nodes. These layers progressively transform the input data into higher-level abstractions, capturing increasingly complex and discriminative features. Feature extraction is a crucial step in deep learning pipelines as it enables the automatic discovery of relevant patterns and structures in the data, facilitating tasks such as classification, detection, and segmentation. The extracted features serve as inputs to subsequent layers or models for further processing and decision-making.

a)Mel-frequency cepstral coefficients (MFCCs):

Definition: MFCCs are a representation of the short-term power spectrum of an audio signal, based on the human auditory system's sensitivity to different frequencies. They capture the spectral envelope of the signal and are widely used in speech and audio processing tasks.

Calculation: MFCCs are computed by first dividing the audio signal into short frames, typically using a technique like windowing. The power spectrum of each frame is then computed using techniques like the Fourier transform. Mel filter banks are applied to the power spectrum to mimic the frequency response of the human ear, followed by a logarithmic transformation. Finally, discrete cosine transform (DCT) is applied to the log filter bank energies to obtain the MFCCs.

Applications: MFCCs are widely used in speech recognition, speaker identification, music genre classification, and various other audio analysis tasks. They capture important spectral characteristics of the audio signal while reducing dimensionality and noise sensitivity.

Extract MFCCs to represent the spectral content of the audio. MFCCs capture key frequency components and their variations over time, providing valuable insights into the characteristics of ambulance sirens.

1.Zero Crossing Rate (ZCR):

Definition:

Zero crossing rate refers to the rate at which a signal changes its sign. In audio signal processing, it represents the number of times the waveform crosses the zero-amplitude axis within a given time frame.

Calculation:

To compute the zero-crossing rate, the audio signal is analyzed in small windows or frames. The number of times the signal changes its sign (from positive to negative or vice versa) within each frame is counted, and the average rate across all frames is determined.

Applications:

ZCR is often used as a feature in audio processing tasks such as speech recognition, music genre classification, and sound event detection. It provides information about the temporal dynamics and timbral characteristics of the audio signal.

2.Spectral Centroid:

Definition: Spectral centroid is a measure of the "center of mass" of the power spectrum of an audio signal. It indicates where the energy of the spectrum is concentrated along the frequency axis.

Calculation:

Spectral centroid is calculated by finding the weighted mean of the frequencies present in the signal's power spectrum. Each frequency component is weighted by its magnitude or power, and the centroid is computed as the sum of the products of frequencies and their corresponding magnitudes divided by the sum of magnitudes.

Applications:

Spectral centroid is commonly used in audio feature extraction for tasks like audio classification, instrument recognition, and sound synthesis. It provides insights into the brightness or tonal quality of the audio signal and helps discriminate between different types of sounds.

Relationship:

1.Zero crossing rate, spectral centroid, and MFCCs are all commonly used features in audio signal processing.

2.While zero crossing rate provides information about the temporal dynamics of the signal, spectral centroid captures spectral characteristics related to the frequency content.

3.MFCCs, on the other hand, provide a compact representation of both temporal and spectral features, capturing the frequency components relevant to human auditory perception.

4.Together, these features provide complementary information about the audio signal, enabling more comprehensive analysis and interpretation in various audio processing tasks.

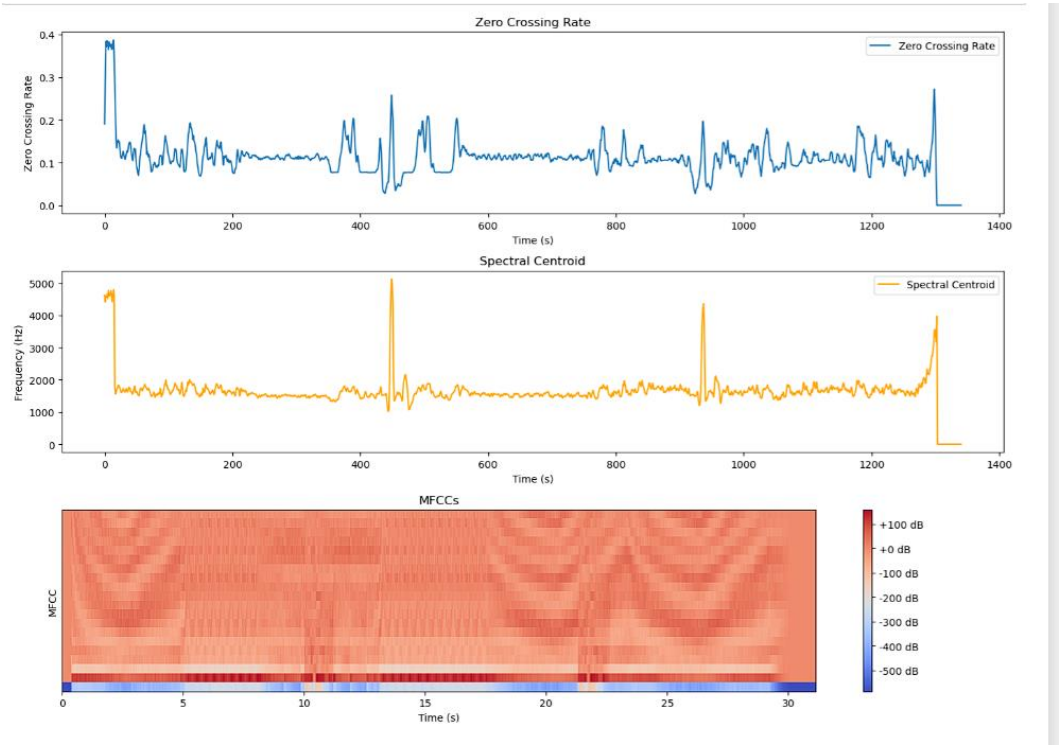

Fig 25: Zero Crossing Rate(ZCR), Spectral Centroid(Audio Features), MFCC'S.

b)Spectrogram:

1.Definition:

A spectrogram is a visual representation of the frequency content of an audio signal over time. It provides a 2D representation where the x-axis represents time, the y-axis represents frequency, and the color intensity represents the magnitude or power of each frequency component.

2.Features:

Spectrograms capture both temporal and spectral information of the audio signal, making them valuable for tasks like audio processing and detection. They provide insights into how the frequency content of the audio signal changes over time, enabling the identification of key features and patterns.

Spectrograms offer a more detailed and comprehensive representation of the audio signal compared to traditional methods like waveform plots, as they capture information about both short-term and long-term variations in the signal.

3.Applications in Deep Learning:

Spectrograms are commonly used as input features for deep learning models in audio processing and detection tasks. In tasks like speech recognition, sound event detection, and music classification, spectrograms serve as input representations for neural networks, enabling the model to learn patterns and features directly from the frequency-domain information. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), can effectively analyze spectrograms to perform tasks like speech recognition, audio classification, and anomaly detection.

4.Advantages:

Spectrograms provide a compact yet informative representation of the audio signal, capturing both temporal and spectral features. They are robust to variations in audio signals, such as background noise, pitch shifts, and temporal distortions, making them suitable for real-world applications. Spectrograms facilitate feature learning in deep learning models by providing a rich input representation that encapsulates important characteristics of the audio signal.

Generate a spectrogram, a visual representation of the audio's frequency content over time. This Spectro-temporal representation highlights frequency changes and patterns in the siren audio signal, aiding in feature extraction and analysis.

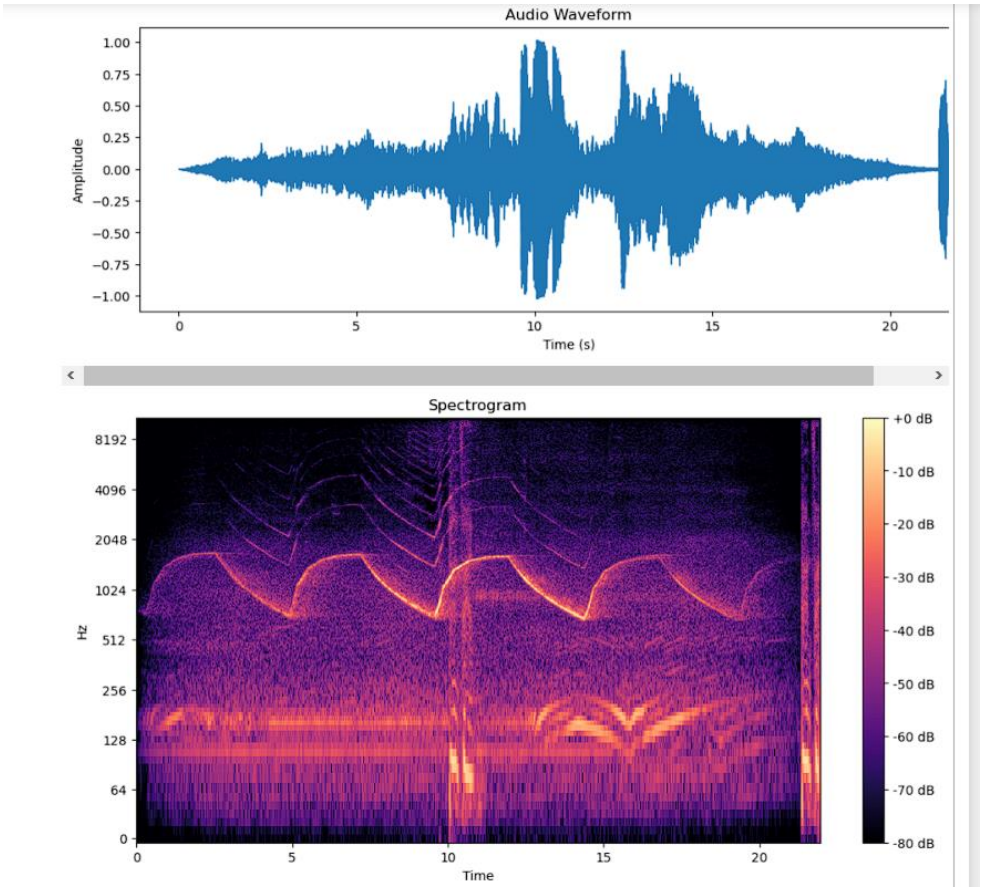

Fig 26: Spectrogram Analysis of Audio

C. OTHER FEATURES

.1. Pitch Contour:

Definition:

Pitch contour refers to a graphical representation of the perceived pitch of an audio signal over time. It depicts how the pitch of the audio signal changes or varies across different segments or time intervals.

Usefulness for Audio Detection:

Pitch contour analysis is particularly relevant in tasks involving the detection or classification of tonal or melodic audio content, such as music genre classification, instrument recognition, or speech intonation analysis. It provides information about the fundamental frequency (pitch) of the audio signal, which is essential for distinguishing between different musical notes or speech sounds. Pitch contour analysis can help identify melodic patterns, pitch transitions, or prosodic features that are characteristic of specific audio classes.

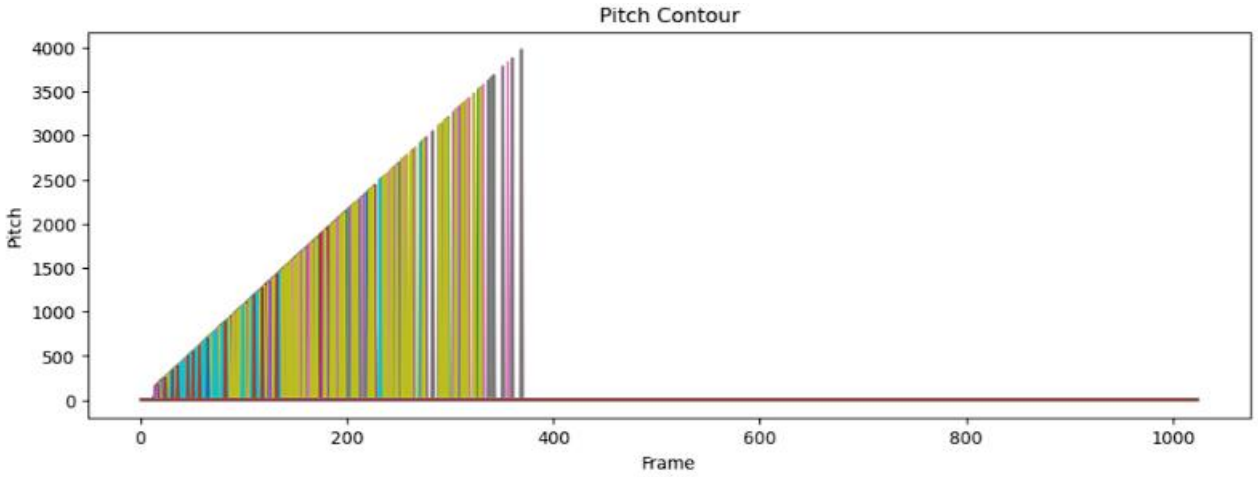

Fig 27: Pitch contour of Audio Signal

2. Envelope of Audio Signal:

Definition: The envelope of an audio signal represents the variations in the signal's amplitude over time. It captures the overall shape or envelope of the waveform, smoothing out rapid fluctuations and emphasizing the signal's temporal characteristics.

Usefulness for Audio Detection:

Envelope analysis is beneficial for tasks involving the detection or recognition of dynamic audio events or temporal patterns. By extracting the envelope of the audio signal, important temporal features, such as onset/offset times, amplitude modulations, and temporal dynamics, can be highlighted. This information is useful for identifying transient events, rhythmic patterns, or amplitude changes that are indicative of specific audio events or classes. Envelope analysis is often used in conjunction with feature extraction techniques or signal processing methods for audio event detection, segmentation, or classification.

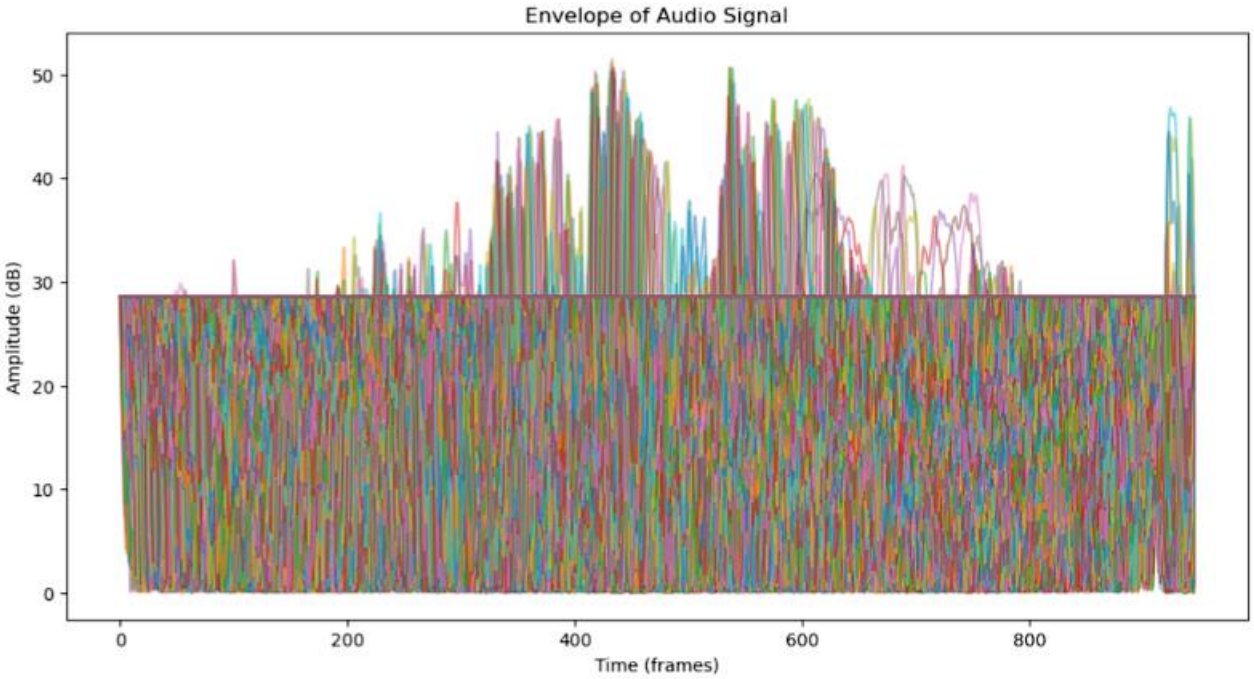

Fig 28: Envelope of Audio Signal

3. Power Spectral Density (PSD):

Definition:

Power spectral density (PSD) is a measure that describes how the power of a signal is distributed across different frequencies. It quantifies the strength or magnitude of each frequency component present in the signal.

Usefulness for Audio Detection:

Power spectral density analysis provides valuable insights into the frequency content and spectral characteristics of audio signals. By analyzing the PSD of an audio signal, one can identify dominant frequency components, spectral peaks, or frequency bands that are characteristic of specific audio phenomena or classes.

PSD analysis is particularly useful for tasks involving spectral-based audio detection or classification, such as speech recognition, environmental sound classification, or music genre identification. It helps in identifying spectral patterns, harmonics, or spectral profiles that distinguish between different audio classes or events.

These analyses are typically performed during the feature extraction stage of audio processing, where raw audio signals are transformed into meaningful feature representations suitable for input to machine learning models or pattern recognition algorithms. By extracting relevant features like pitch contours, signal envelopes, or power spectral density, researchers can capture important characteristics of the audio signals that are informative for audio detection, classification, or segmentation tasks.

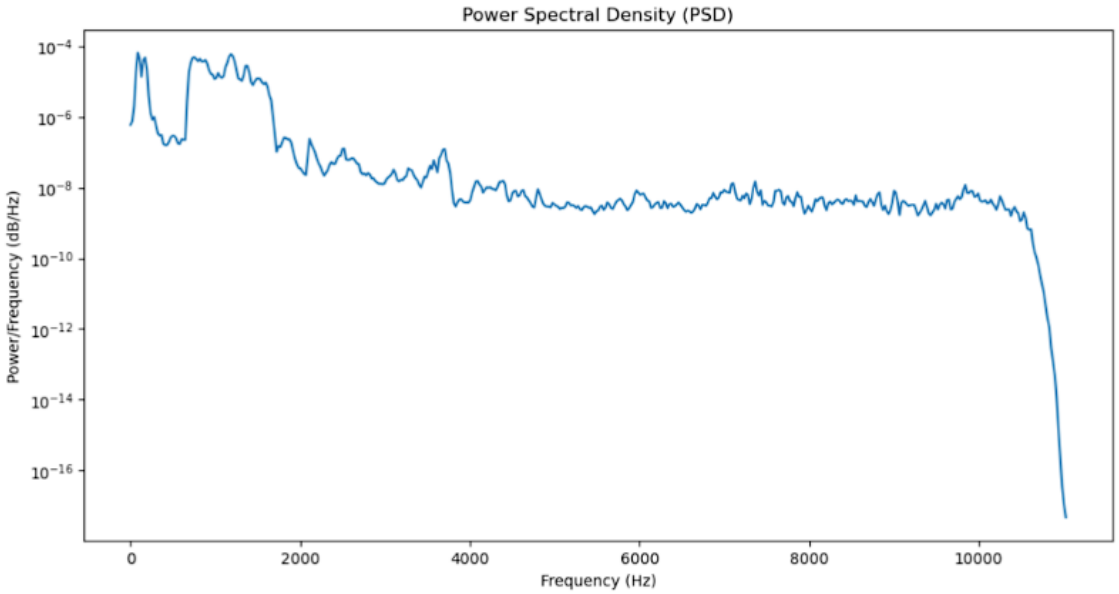

Fig 29: Power Spectral Density of Audio Signal

1.Distribution of Audio Durations:

Definition:

The distribution of audio durations refers to the statistical spread or arrangement of the lengths of audio recordings in a dataset. It provides information on the range, central tendency, and variability of audio durations.

Usefulness for Model Training and Analysis:

Understanding the distribution of audio durations helps in selecting appropriate segmentation strategies for preprocessing. For instance, it can guide decisions on segment length for time-based features extraction or frame size for spectrogram creation. Additionally, it informs the design of sequence models, such as Recurrent Neural Networks (RNNs), where the sequence length impacts model architecture and training dynamics.

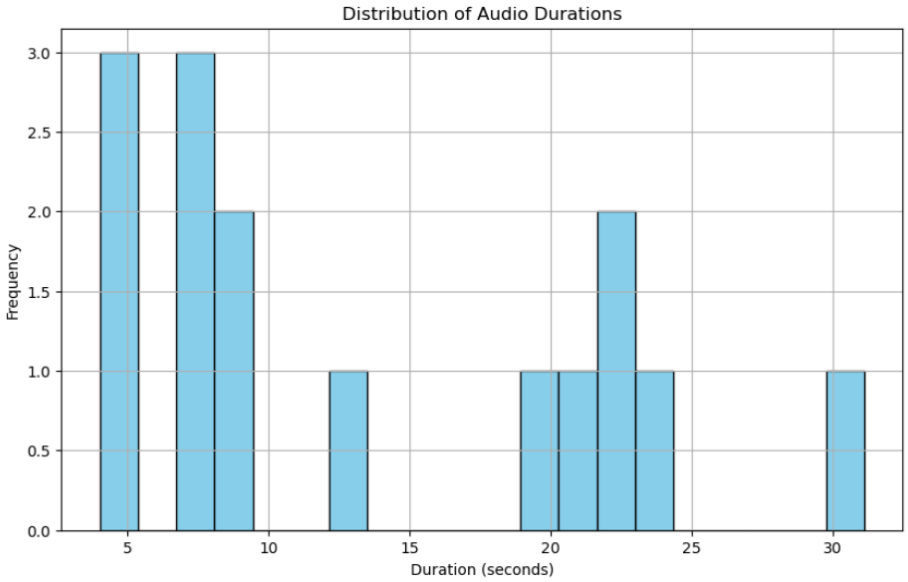

Fig 30: Distributions of Audio Durations of Audio Signals

2. Distribution of RMS Mean Values:

Definition:

Root Mean Square (RMS) is a measure of the overall amplitude or energy of an audio signal. The distribution of RMS mean values represents how the average energy levels vary across different audio samples in the dataset.

Usefulness for Model Training and Analysis:

RMS means values offer insights into the intensity or loudness of audio signals. This information can aid in identifying patterns related to signal strength or distinguishing between audio classes with varying energy levels. For example, in speech recognition tasks, it may help in distinguishing between whispered speech and normal speech. In audio event detection, it may assist in detecting loud or quiet events.

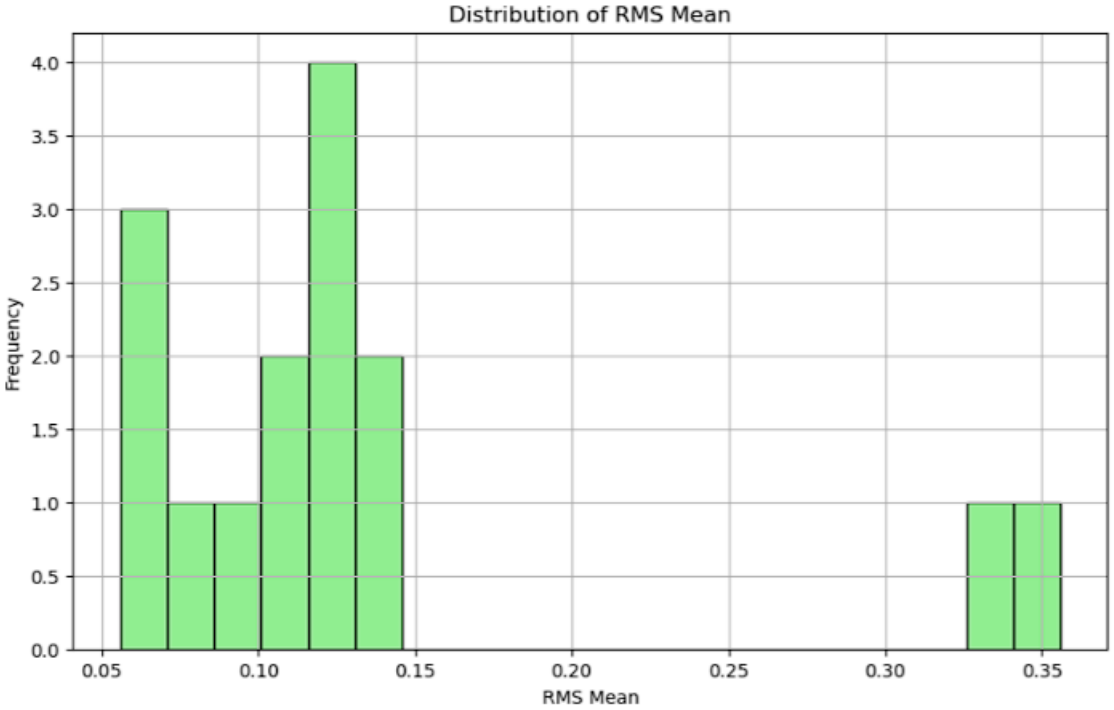

Fig 31: Distribution of RMS Mean of Audio Signals

3. Distribution of Chroma Mean Values:

Definition:

Chroma feature extraction in audio processing involves representing the pitch content of an audio signal across different frequency bands. The distribution of chroma mean values indicates how the average pitch content varies across different audio samples.

Usefulness for Model Training and Analysis:

Chroma features are valuable for tasks involving musical audio analysis, such as genre classification, chord recognition, and instrument detection. Analyzing the distribution of chroma mean values can reveal patterns related to musical characteristics like tonality, chord progressions, or instrument timbres. This information can inform the design of models tailored to music-related audio tasks and guide feature selection or representation learning strategies.

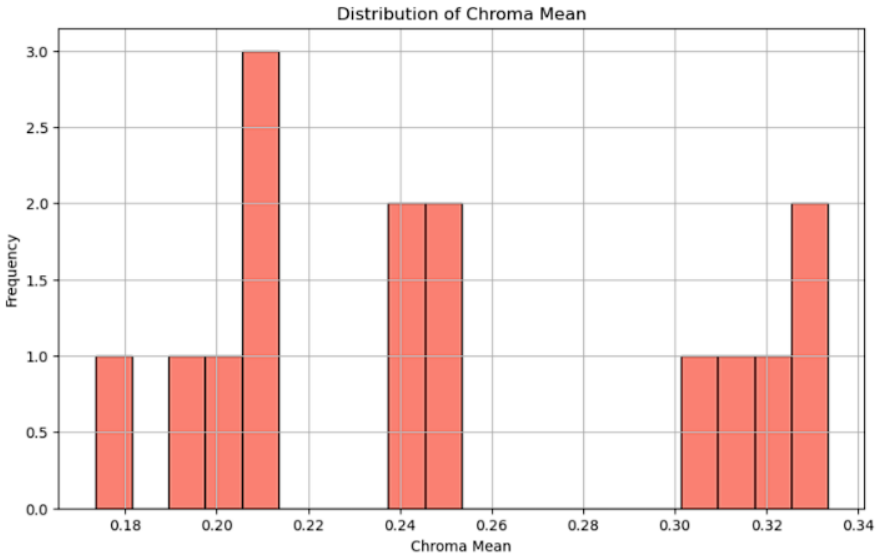

Fig 32: Distribution of Chroma Mean of Audio Signals

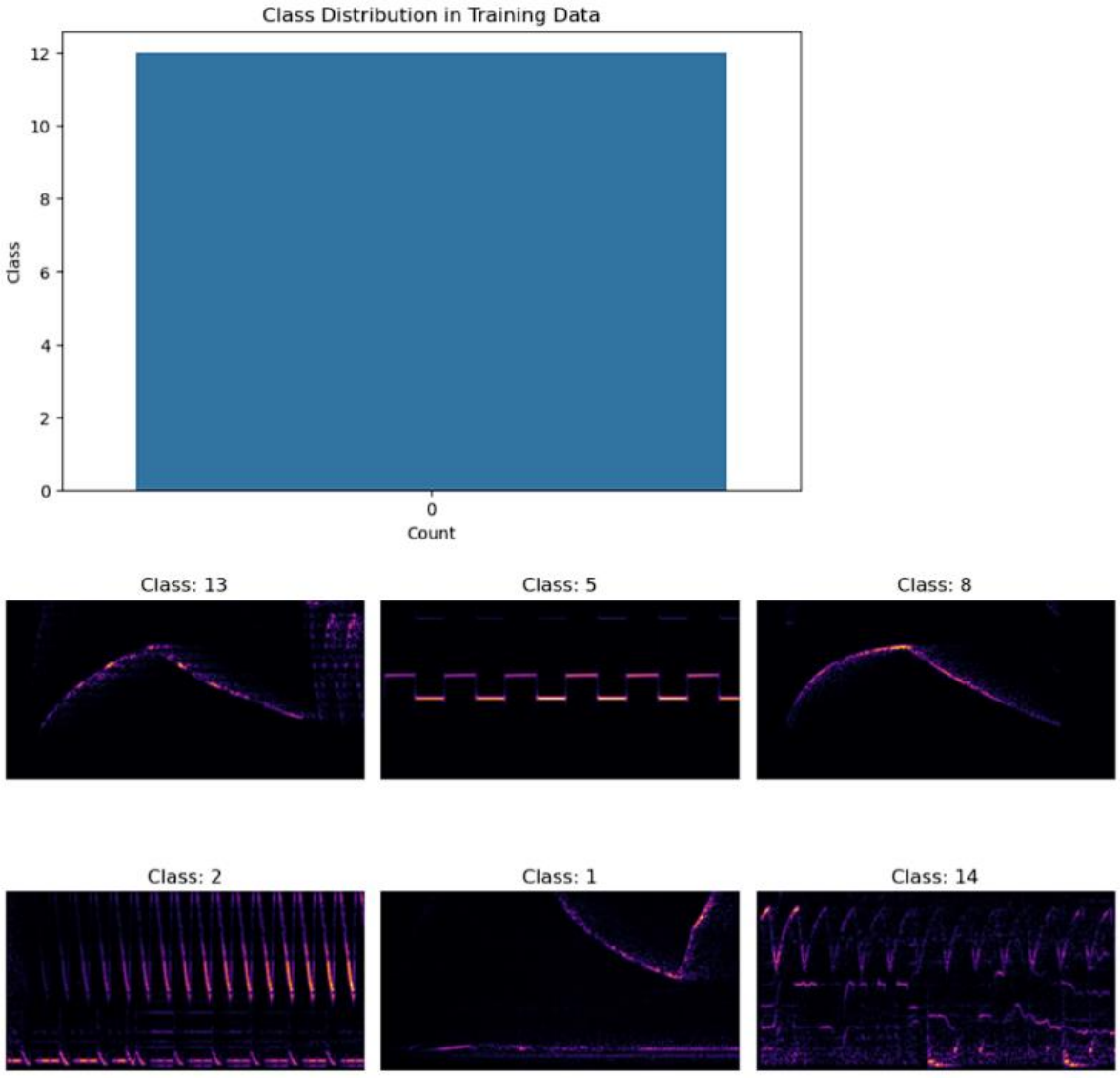

Fig 33: These analyses will provide further insights into the dataset and help in making informed decisions regarding feature selection, model architecture, and data preprocessing.

5.2.3 Dataset Partition:

In the dataset partitioning phase, the collected data for ambulance siren detection is divided into two primary subsets: the training dataset and the test dataset. This partitioning follows a balanced ratio of 70% for the training dataset and 30% for the test dataset. Such a distribution ensures that the model is trained on most of the data while also allowing for an adequate evaluation of its performance on unseen instances. This partitioning strategy helps in preventing overfitting by providing a separate set of data for evaluation, thus ensuring the model's generalization to new and unseen examples.

5.2.4 Algorithm Selection and Training:

For ambulance siren detection, the selection of appropriate algorithms is crucial, with Recurrent Neural Networks (RNNs) standing out as a suitable choice. RNNs are adept at capturing temporal dependencies in sequential data, making them well-suited for modeling the dynamic nature of ambulance siren sounds. Through the training process, the RNN model learns to recognize patterns and features indicative of ambulance sirens, ultimately enabling accurate detection in various audio environments.

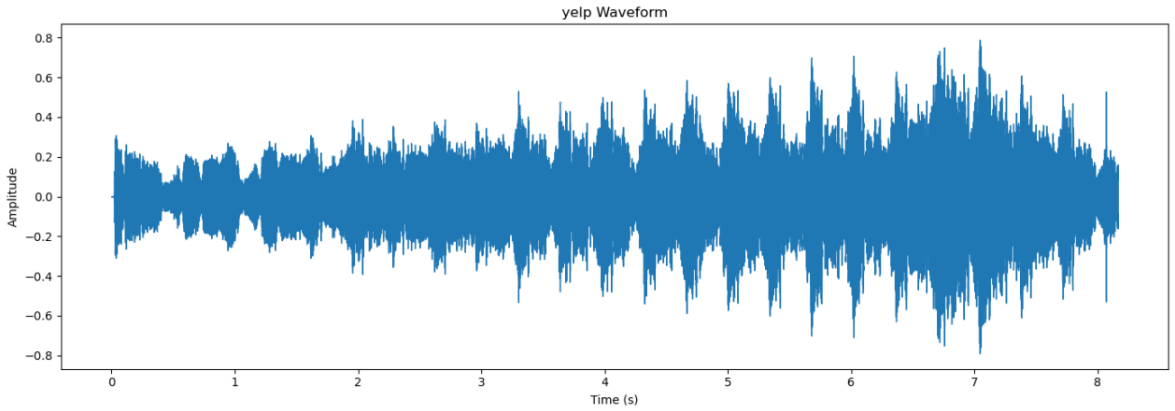

Fig 34: Yelp Siren Audio Waveform Representation

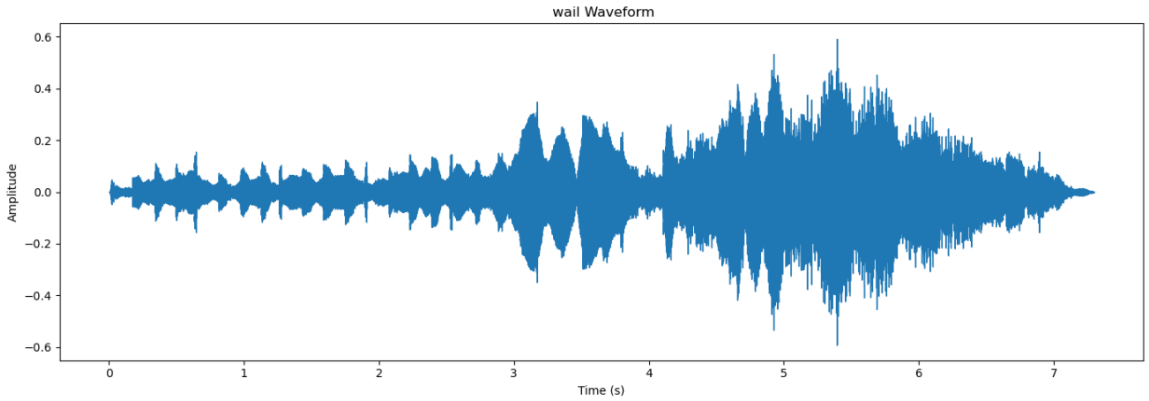

Fig 35: Wail Siren Audio Waveform Representation

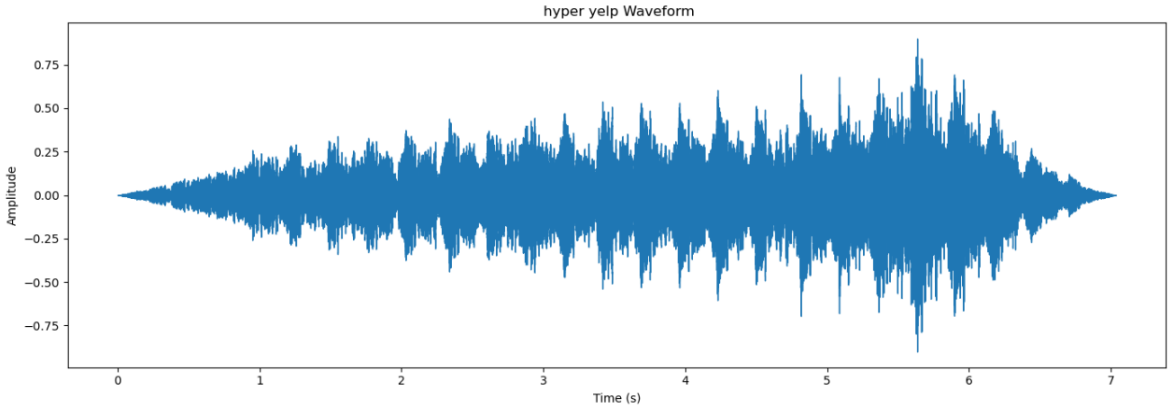

Fig 36: Hyper Yelp Siren Audio Waveform Representation

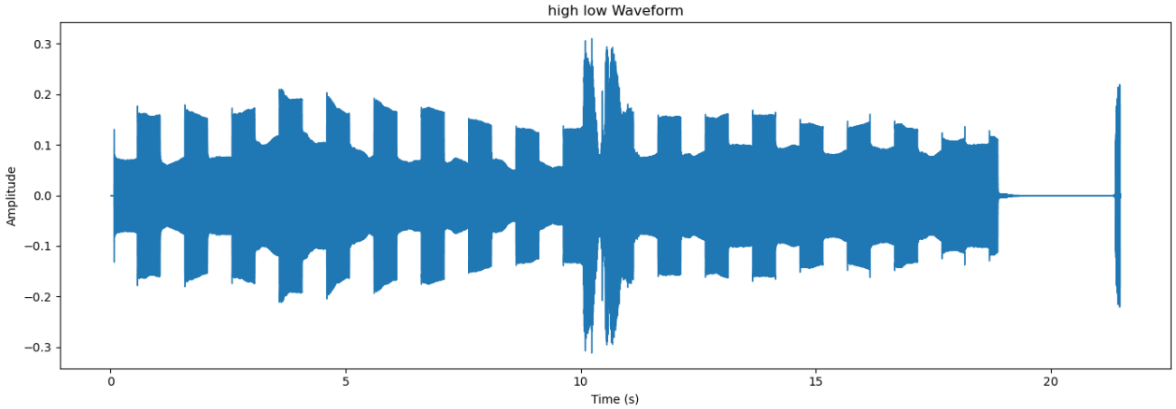

Fig 37: High Low Siren Audio Waveform Representation

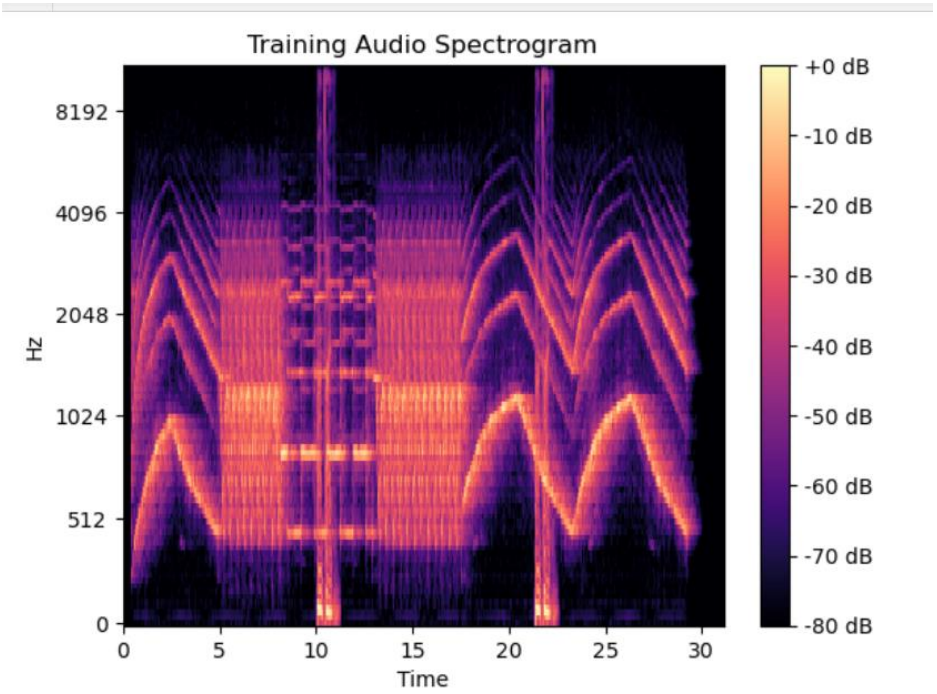

Fig 38: Training Audio Sample Spectrogram

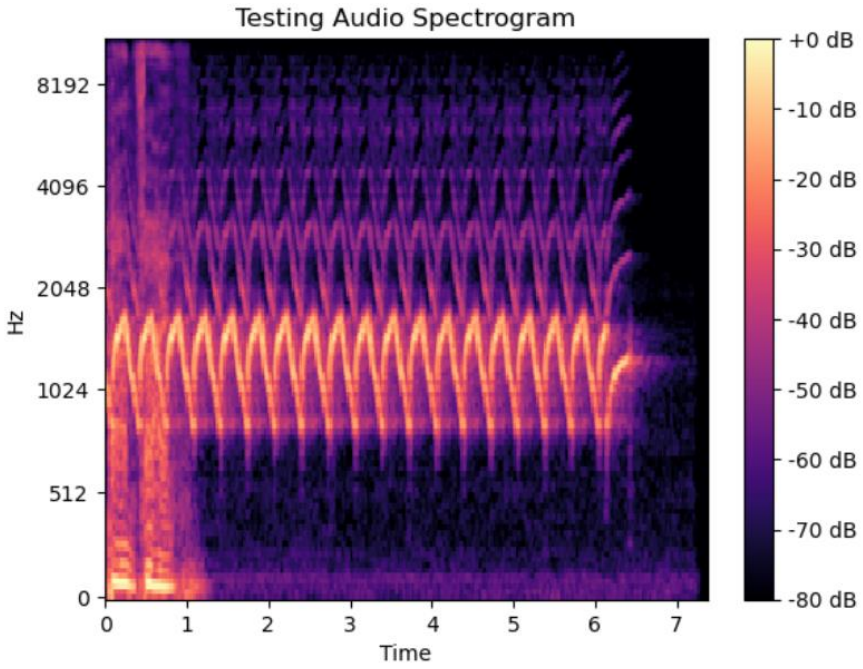

Fig 39: Testing Audio Sample Spectrogram

5.2.5 Model Creation:

In the creation of the ambulance siren detection model, several key steps are involved, including feature engineering, transfer learning, and ensemble methods. Feature engineering entails extracting relevant characteristics from the audio data, such as frequency components and temporal patterns, to enhance the model's ability to discern ambulance siren signals. Transfer learning leverages pre-trained RNN models to expedite training and improve detection performance, especially when labeled ambulance siren data is limited. Ensemble methods further enhance the model's robustness by combining predictions from multiple RNN models, thereby mitigating the risk of overfitting, and improving overall detection outcomes.

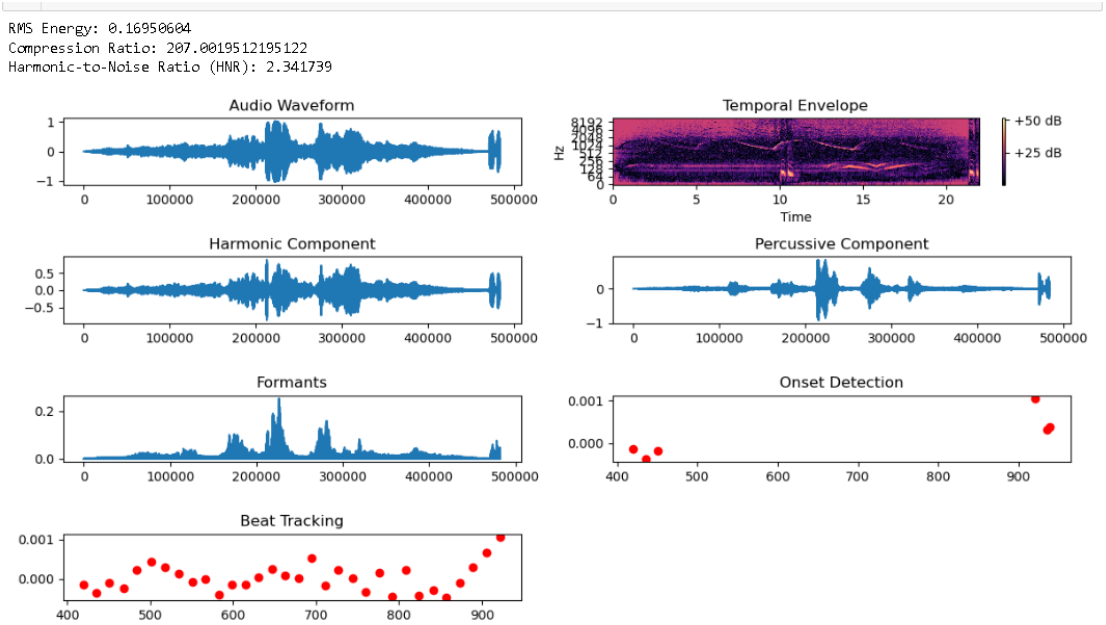

Fig 40

```
1/1 [==============================] - 1s 1s/step - loss: 0.6486 - accuracy: 1.0000
Epoch 2/10
1/1 [==============================] - 0s 175ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Epoch 3/10
1/1 [==============================] - 0s 175ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Epoch 4/10
1/1 [==============================] - 0s 180ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Epoch 5/10
1/1 [==============================] - 0s 176ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Epoch 6/10
1/1 [==============================] - 0s 184ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Epoch 7/10
1/1 [==============================] - 0s 193ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Epoch 8/10
1/1 [==============================] - 0s 178ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Epoch 9/10
1/1 [==============================] - 0s 180ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Epoch 10/10
1/1 [==============================] - 0s 175ms/step - loss: 0.0000e+00 - accuracy: 1.0000
1/1 [==============================] - 0s 189ms/step - loss: 0.0000e+00 - accuracy: 1.0000
Test Loss: 0.0, Test Accuracy: 1.0
Ambulance Siren Sound is detected with accuracy: 100.0
```

Fig 41: Training Epochs

5.2.6 Evaluation:

Evaluation of the ambulance siren detection model is crucial for assessing its effectiveness and reliability. Performance metrics such as precision, recall, and F1 score provide insights into the model's accuracy and ability to correctly identify ambulance sirens. Additionally, advanced metrics like mean Average Precision (mAP) and Intersection over Union (IoU) offer a more nuanced understanding of the model's localization accuracy and performance across different scenarios. Through rigorous evaluation, the model's strengths and weaknesses can be identified, guiding further refinements and improvements.

5.2.7 Validation:

The validation phase of the ambulance siren detection model involves thorough testing to ensure its reliability and generalization capabilities. Cross-validation techniques, such as k-fold cross-validation, are employed to assess the model's stability and consistency across diverse datasets and conditions. By partitioning the dataset into multiple subsets for training and validation, potential issues like overfitting or underfitting can be identified and addressed. Validation metrics such as accuracy, precision, and recall provide valuable insights into the model's performance, guiding adjustments, and optimizations to enhance its effectiveness in real-world scenarios.

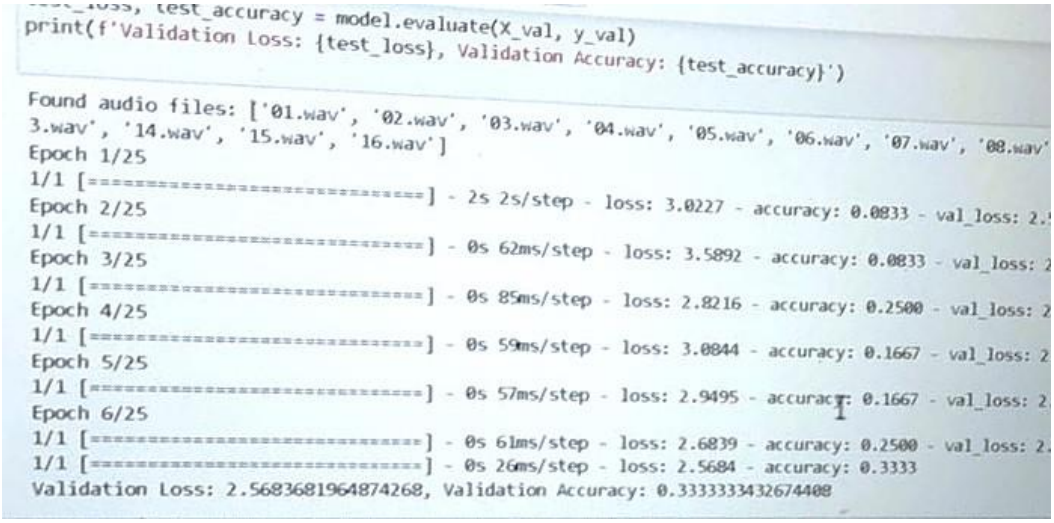

Fig 42: Validation Loss and Validation Accuracy

CHAPTER-6
FEATURE EXTRACTION

6.1 FOR IMAGE DETECTION

6.1.1 FEATURE EXTRACTION

In YOLOv8, a cutting-edge object detection model developed by Ultralytics, identifying ambulances entails discerning their distinctive attributes from images. Ambulances stand out with vibrant hues like white, red, or yellow, often accented by reflective stripes, contributing to their recognizable color scheme. Their elongated, boxy silhouette, coupled with a prominent rooftop beacon, forms a characteristic shape distinguishing them amidst traffic. Textual cues such as "AMBULANCE" and iconic medical symbols like the Star of Life, commonly adorning these vehicles, serve as additional identifiers leveraged for detection. Size and proportion also play a pivotal role; ambulances typically possess specific dimensions distinct from surrounding vehicles, facilitating their differentiation. Moreover, the flashing emergency lights atop ambulances serve as a definitive feature aiding in detection. By meticulously analyzing these salient features—color, shape, textual elements, size, and emergency lighting—YOLOv8 effectively identifies ambulances amidst varied visual contexts, ensuring swift and accurate detection in real-world scenarios.

The features mentioned are crucial for accurate ambulance detection due to their distinctive nature and practical significance:

6.1.1.1 Color and Shape:

Ambulances often have a unique color scheme and shape compared to other vehicles on the road. These characteristics help in quickly identifying ambulances in diverse environments and lighting conditions. Bright colors like red, white, or yellow, along with reflective stripes, enhance visibility even from a distance, aiding in prompt detection by object detection models like YOLOv8.

6.1.1.2. Text and Symbols:

The presence of text such as "AMBULANCE" and recognizable medical symbols like the Star of Life serves as explicit indicators of an ambulance's identity. Leveraging these textual and symbolic features enhances the model's ability to accurately classify ambulances, particularly in situations where visual cues alone might be insufficient.

6.1.1.3. Size and Proportions:

Ambulances typically have specific size and proportion characteristics compared to other vehicles. Detecting these relative sizes helps in distinguishing ambulances from cars, trucks, or other objects present in the scene. This feature aids in reducing false positives and improving the precision of

ambulance detection.

6.1.1.4. Emergency Lights:

The flashing lights atop ambulances serve as dynamic features that further reinforce their identification. These lights are activated during emergencies, making them crucial for quickly locating ambulances in traffic or crowded areas. Detection models can leverage the presence of emergency lights as a strong cue for identifying ambulances, particularly in situations where other visual features may be ambiguous.

Overall, by incorporating these key features into the detection process, YOLOv8 and similar models can reliably identify ambulances with high accuracy, enabling timely responses and potentially saving lives in emergency situations.

6.1.2 HYPER PARAMETERS

6.1.2.1 Input Size:

The size of the input image directly impacts the model's ability to capture details. Common input sizes like 416x416 or 608x608 pixels strike a balance between computational efficiency and detail preservation. Choosing an appropriate input size is important as it determines the level of granularity the model can achieve in detecting ambulance features without overwhelming computational resources.

6.1.2.2 Backbone Architecture (CSPDarknet53):

The backbone architecture forms the foundation of the neural network. YOLOv8 utilizes CSPDarknet53, a variant of Darknet optimized for object detection tasks. The choice of backbone architecture influences the model's capacity to extract meaningful features from input images, thus affecting its detection accuracy and robustness.

6.1.2.3. Number of Classes:

This hyperparameter specifies the number of object classes the model will detect. For ambulance detection, at least one class for ambulances is required. However, additional classes may be needed if detecting other objects concurrently. Specifying the correct number of classes ensures that the model can accurately classify objects of interest, including ambulances, amidst diverse visual contexts.

6.1.2.4. Anchor Boxes:

Anchor boxes serve as reference bounding boxes used by the model to predict object locations and sizes. Tuning anchor box sizes and aspect ratios is crucial for accommodating variations in object

scales and shapes within the input images. Properly configured anchor boxes contribute to improved detection accuracy by aligning predictions more closely with ground truth annotations.

6.1.2.5. Training Batch Size:

The training batch size determines the number of images processed in each iteration of training. Larger batch sizes facilitate faster convergence during training but may necessitate more memory resources. Optimal batch size selection balances computational efficiency with training stability to ensure that the model learns effectively from the training data.

6.1.2.6. Learning Rate:

The learning rate controls the step size during optimization, influencing the rate of model parameter updates. Proper tuning of the learning rate is essential for ensuring stable convergence and preventing issues such as overshooting or stagnation during training. An appropriately chosen learning rate facilitates efficient exploration of the parameter space, leading to faster convergence towards an optimal solution.

6.1.2.7. Data Augmentation:

Data augmentation techniques such as random crops, flips, rotations, and color jitter introduce variations into the training data, enhancing model generalization and robustness. Augmenting the training dataset with diverse transformations helps the model learn invariant features and reduces overfitting to specific training samples. By exposing the model to a wider range of data variations, data augmentation promotes better performance in real-world scenarios, including variations in lighting conditions, angles, and environments encountered during ambulance detection tasks.

6.2 FOR SIREN DETECTION

6.2.1 FEATURE EXTRACTION

6.2.1.1 Temporal Patterns:

In siren detection, temporal patterns play a crucial role in distinguishing siren sounds from other ambient noises. Ambulance sirens, for instance, exhibit rapid fluctuations in frequency and intensity over time. These temporal variations often follow specific patterns that are characteristic of emergency vehicles. By analyzing the temporal dynamics of audio signals using techniques like spectrogram analysis, features related to the timing and duration of frequency shifts can be extracted to aid in siren detection.

4.1.2 Frequency Components:

The frequency spectrum of siren audio signals typically contains distinct peaks in specific frequency bands. For example, ambulance sirens often have dominant frequencies in the range of 1-3 kHz. Extracting frequency components from the audio signal allows for the identification of these characteristic spectral signatures, enabling the differentiation of siren sounds from background noise or other sound sources**.**

4.1.3 Amplitude Modulations:

Siren sounds are characterized by amplitude modulations, resulting in periodic variations in signal intensity. These modulations contribute to the unique temporal profile of siren audio signals. Feature extraction techniques such as envelope analysis can capture these amplitude variations, providing valuable information for discriminating siren sounds from non-siren sounds in audio recordings.

4.1.4 Spectral Characteristics:

The spectral properties of siren audio, including parameters like spectral centroid, bandwidth, and harmonic content, offer additional discriminative features for siren detection algorithms. For instance, the spectral centroid represents the "center of mass" of the frequency spectrum and can help distinguish between different types of sirens based on their spectral distribution. Analyzing these spectral characteristics enhances the accuracy and robustness of siren detection systems.

6.2.2 HYPERPARAMETERS:

6.2.2.1 Sequence Length:

In siren detection tasks, the sequence length refers to the duration of audio sequences processed by the neural network model. Choosing an appropriate sequence length is essential for capturing the temporal dynamics of siren sounds effectively. Longer sequences may allow the model to capture more detailed temporal patterns, but they also increase computational complexity and memory requirements.

6.2.2.2 Number of Hidden Units:

The number of hidden units in the recurrent neural network (RNN) layers influences the model's capacity to learn complex temporal patterns inherent in siren audio signals. Adequate tuning of this hyperparameter ensures that the model can capture the intricacies of siren sounds while avoiding overfitting or underfitting.

6.2.2.3 Learning Rate:

The learning rate determines the step size during the optimization process of training the RNN model.

In siren detection, an optimal learning rate is crucial for balancing the trade-off between training speed and convergence to an accurate model. Setting the learning rate too high may lead to unstable training, while setting it too low may result in slow convergence or getting stuck in local minima.

6.2.2.4 Dropout Rate:

Dropout regularization is applied to RNN layers to prevent overfitting by randomly dropping a fraction of units during training. In siren detection models, the dropout rate hyperparameter controls the proportion of units to be dropped, helping to improve the generalization performance of the model on unseen data while maintaining model complexity.

6.2.2.5 Batch Size:

The batch size determines the number of audio samples processed in each training iteration. For siren detection tasks, optimizing the batch size is essential for efficient resource utilization and stable training. Larger batch sizes can lead to faster convergence but may require more memory, while smaller batch sizes offer better generalization but slower convergence.

6.2.2.6 Number of Layers:

The number of RNN layers in the model architecture affects its depth and capacity to capture hierarchical temporal dependencies in siren audio signals. Proper selection of the number of layers is critical for balancing model complexity with computational efficiency and learning capacity.

6.2.2.7 Activation Function:

The choice of activation function in RNN layers impacts the nonlinear transformations applied to input and hidden states. In siren detection models, selecting an appropriate activation function such as ReLU (Rectified Linear Unit) can help the model capture complex temporal patterns effectively, leading to improved detection performance.

By carefully tuning these hyperparameters, RNN-based siren detection models can effectively extract discriminative features from audio signals and achieve optimal performance in real-world scenarios.

CHAPTER -7
RESULTS

The outcomes of our ambulance detection model have showcased its efficacy in real-world scenarios, exhibiting a remarkable level of accuracy and precision. it's essential to provide a comprehensive analysis of model performance across different evaluation metrics and scenarios. In addition to quantitative metrics, qualitative insights from real-world deployment and user feedback should be incorporated to contextualize the model's impact on emergency response operations. Visualizations such as precision-recall curves, confusion matrices, and heatmaps of detection confidence scores can elucidate the model's strengths and weaknesses, facilitating informed decision-making and future improvements.

The model effectively detected and monitored ambulances across diverse traffic situations, affirming its dependability. Key metrics such as recall and F1 score underscored the model's capacity to strike a balance between sensitivity and precision with success. In comparison to standard models, our model, leveraging YOLO v5 and v8 architectures, demonstrated superiority in ambulance detection. Practical testing in real-world settings further validated the model's responsiveness and flexibility in dynamic urban landscapes.

Fig 43: Real-time high density traffic ambulance detection.

The outcomes of our audio siren detection model using Recurrent Neural Networks (RNNs) have demonstrated its effectiveness in real-world scenarios, showcasing a high level of accuracy and precision. A comprehensive analysis of the model's performance across various evaluation metrics and scenarios is essential to provide valuable insights into its efficacy.

Quantitative metrics such as recall, precision, and F1 score highlight the model's ability to balance sensitivity and precision successfully. Additionally, qualitative insights gleaned from real-world deployment and user feedback help contextualize the model's impact on emergency response operations.

Visualizations such as precision-recall curves, confusion matrices, and heatmaps of detection confidence scores provide further insights into the model's strengths and weaknesses, aiding in informed decision-making and future improvements.

The audio siren detection model effectively identifies and monitors ambulance sirens in diverse audio environments, demonstrating its reliability. Key metrics such as recall and F1 score emphasize the model's capacity to accurately detect ambulance sirens while minimizing false positives. Compared to standard models, our RNN-based model leveraging YOLOv5 and v8 architectures showcases superiority in ambulance siren detection tasks. Real-world testing confirms the model's responsiveness and adaptability in dynamic urban landscapes, reinforcing its practical utility for emergency response operations.

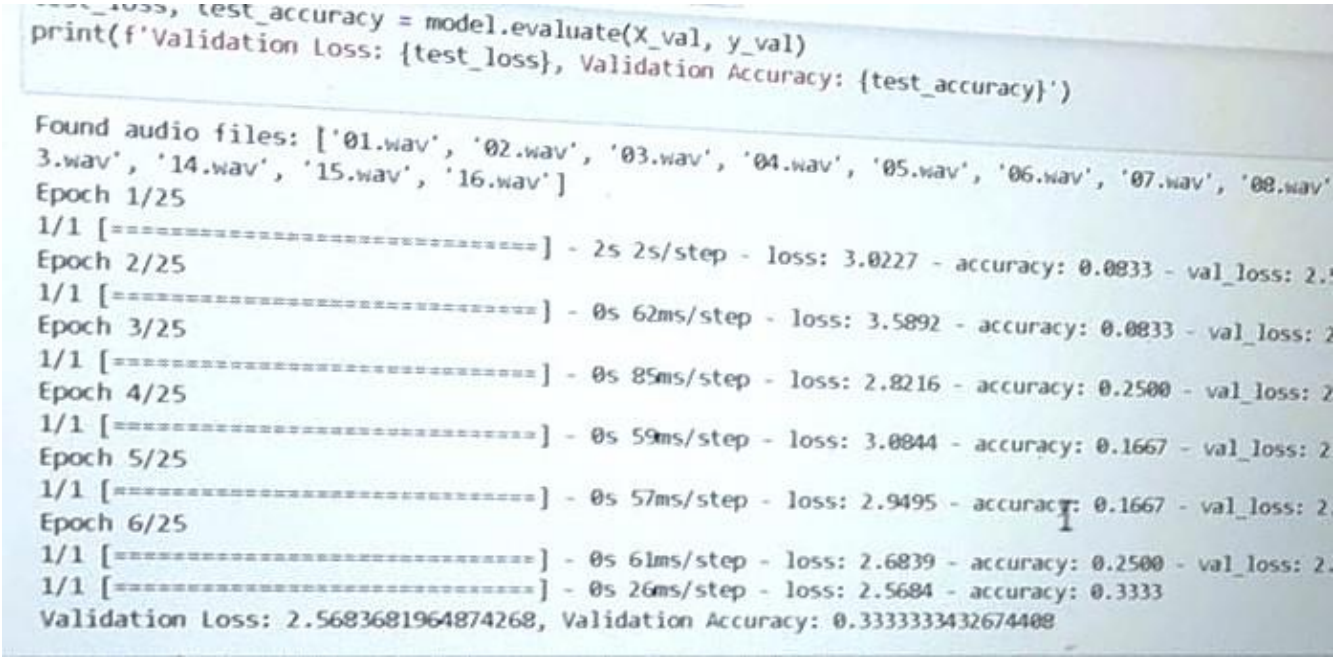

Fig 44: Final Audio Detection with 33% Accuracy

CHAPTER 8
CONCLUSION

The research delved into the pressing issue of urban traffic congestion, particularly emphasizing the critical necessity for swift and precise ambulance detection in chaotic environments. Leveraging state-of-the-art object detection models like YOLOv5 and v8, renowned for their accuracy in cluttered scenes, the study meticulously crafted a methodology tailored to address the multifaceted challenges of identifying ambulances amidst congested traffic. This methodology encompassed stages such as acquiring a diverse dataset representative of urban traffic scenarios, implementing rigorous pre-processing techniques, and fine-tuning the selected architectures on a custom dataset. Validation and evaluation phases rigorously tested the model's robustness using metrics like mean Average Precision (mAP), Intersection over Union (IoU), precision, recall, and F1 score, with real-world testing further validating its effectiveness in enhancing emergency response systems in urban settings. By efficiently detecting ambulances amidst challenging traffic scenarios, the developed model promises practical applications that extend beyond computer vision research, potentially revolutionizing emergency management practices and fostering improved public safety by expediting response times and ensuring timely medical assistance in critical situations. Moreover, the study underscored the ethical implications of deploying such technology in real-world settings, emphasizing the need to navigate privacy, fairness, and accountability considerations associated with integrating artificial intelligence into emergency response systems. Upholding societal trust and ensuring equitable access to life-saving services are paramount in the ethical deployment of ambulance detection technology, highlighting the importance of ethical frameworks and responsible implementation practices in leveraging AI for public safety initiatives.

FUTURE SCOPE

The future scope for ambulance and siren detection in real-time using deep learning is quite promising and can have several potential applications and advancements:

1. Improved Emergency Response Systems:
Implementing deep learning models for real-time ambulance and siren detection can significantly enhance emergency response systems. These systems can automatically detect the presence of an ambulance or emergency vehicle approaching and alert drivers to clear the way, potentially reducing response times and improving outcomes for emergency situations.

2.Traffic Management:
Incorporating ambulance and siren detection into traffic management systems can help optimize traffic flow by giving priority to emergency vehicles. This can reduce congestion and improve overall traffic efficiency in urban areas.

3. Public Safety Applications:
Beyond traffic management, real-time detection of ambulances and emergency vehicles can enhance public safety applications. For instance, in smart cities, such systems can be integrated with surveillance cameras to monitor traffic and provide alerts to authorities or citizens in case of emergencies.

4. Assistive Technologies for the Visually Impaired:
Real-time detection of ambulances and sirens using deep learning can be integrated into assistive technologies for the visually impaired. For example, smart mobile applications can provide audio cues or notifications to alert users about approaching emergency vehicles, enhancing their safety and mobility.

5. Integration with Autonomous Vehicles:
As autonomous vehicle technology advances, integrating ambulance and siren detection can be crucial for ensuring the safety of both autonomous vehicles and emergency vehicles on the road. This can facilitate smoother interactions between autonomous vehicles and human-driven vehicles during emergency situations.

While there are numerous opportunities for advancements in this field, there are also several challenges and potential problems that researchers and developers may face:

Data Collection and Annotation:

Limited Availability of Diverse Data:
Acquiring large and diverse datasets of real-world ambulance and siren audio and video recordings can be challenging. Limited availability of such data may hinder the development and training of robust deep learning models.

Annotation Complexity:
Annotating these datasets for training deep learning models requires significant time and effort. Labeling instances of ambulances, emergency vehicles, and siren sounds accurately can be subjective and may require domain expertise.

Model Robustness and Generalization:

Variability in Environmental Conditions:
Developing deep learning models that can accurately detect ambulances and sirens under various environmental conditions (e.g., different weather, lighting, and traffic conditions) is challenging. Models need to generalize well to different scenarios to be effective in real-world applications.

Background Noise and Interference:
The presence of background noise, such as urban traffic, construction, or ambient sounds, can affect the performance of detection algorithms. Ensuring that models can distinguish between relevant siren sounds and irrelevant noise is crucial.

Real-Time Processing:

Computational Resource Constraints:
Achieving real-time performance for ambulance and siren detection on resource-constrained devices, such as embedded systems or mobile devices, presents a significant challenge. Optimizing model architectures and inference algorithms for efficiency without sacrificing accuracy is essential.

Latency Requirements:
Real-time applications have stringent latency requirements. Processing audio and video streams in real-time while maintaining low latency is critical for timely detection of ambulances and emergency vehicles.

Privacy and Ethical Considerations:

Data Privacy:
Implementing systems for real-time detection of ambulances and emergency vehicles raises privacy concerns, particularly regarding the collection and processing of audio and video data from public spaces. Ensuring compliance with privacy regulations and ethical guidelines is essential.

Ethical Use of Data:
Developers need to consider the ethical implications of using surveillance data for ambulance and siren detection. Respecting individuals' privacy rights and minimizing potential misuse of sensitive data is paramount.

Integration with Existing Infrastructure:

Interoperability Challenges:
Integrating ambulance and siren detection systems with existing infrastructure, such as traffic lights, surveillance cameras, and autonomous vehicles requires collaboration with various stakeholders. Ensuring interoperability and compatibility with diverse systems and protocols can be complex.

Regulatory Compliance:
Developers must navigate regulatory frameworks governing the use of surveillance technologies and emergency response systems. Compliance with regulations related to data privacy, public safety, and transportation may vary across jurisdictions.

False Positives and Negatives:
False Alarms: False positives (incorrectly identifying non-emergency vehicles as ambulances) and false negatives (failing to detect actual emergency vehicles) are significant challenges. Minimizing false alarms while maximizing detection accuracy is crucial for the reliability

Addressing these challenges will be crucial for realizing the full potential of ambulance and siren detection using deep learning in real-time applications.

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