iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: III Month of publication: March 2025

DOI: https://doi.org/10.22214/ijraset.2025.67990

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue III Mar 2025- Available at www.ijraset.com

Ambulance and Fire-Engine Detection for Allowing Path to Them Using Artificial Intelligence

Swarup B. Sarjine[1], Prajwal V. Shingare[2], Mahendra B. Gadhave[3], Harshal C. Jondhale[4]
Department of Computer Engineering, Jaihind Polytechnic, Kuran, Pune

Abstract: The increasing number of vehicles on the road has led to severe traffic congestion, especially in densely populated nations such as India and Japan. The lack of dedicated emergency lanes on many highways further exacerbates the difficulty for ambulances and fire engines to navigate through traffic, often resulting in life-threatening delays. To address this issue, this paper presents an image processing-based system for real-time ambulance and fire engine detection, coupled with an alert mechanism to notify other road users via digital boards at upcoming intersections. The proposed system leverages the ResNet deep learning model to accurately detect emergency vehicles at designated traffic points. Upon detection, a real-time alert message is displayed on digital boards at approaching junctions, ensuring that other vehicles are aware of the presence of an emergency vehicle and can take necessary action to clear the way. This automated system enhances response times for emergency services, ultimately improving the efficiency of life-saving interventions.
Keywords: Image processing, Traffic congestion, Emergency vehicle alert, ResNet deep learning, Real-time detection, Digital board notification.

I. INTRODUCTION

Traffic congestion in urban areas is a persistent issue that not only affects daily commutes but also creates life-threatening delays for emergency vehicles such as ambulances and fire engines. In highly populated cities, fixed traffic signal timings fail to accommodate urgent medical and fire emergencies, leading to significant delays in reaching hospitals or disaster sites. Studies indicate that reducing ambulance response time can drastically improve survival rates for critically injured patients [1]. According to research, even a one-minute delay in medical intervention can lead to a substantial increase in pre-hospital mortality rates [2][3]. The inability of emergency vehicles to manoeuvrer swiftly through traffic is a pressing concern, particularly in countries with high vehicular density such as India, Japan, and other rapidly developing nations.

To tackle this issue, researchers have explored various AI-driven traffic management techniques aimed at detecting emergency vehicles in real time and alerting relevant authorities and road users. AI-based image processing techniques have been increasingly adopted due to their ability to accurately identify ambulances and fire engines through video surveillance. Object detection models such as YOLO (You Only Look Once) have demonstrated high efficiency in recognizing emergency vehicles even in challenging conditions like low-light environments, adverse weather, and congested roads [4][5]. Convolutional Neural Networks (CNNs) have also been utilized to enhance vehicle detection accuracy, providing reliable identification of ambulances amid diverse traffic scenarios [6].

One of the most effective methods currently being researched is the use of real-time alert systems that display warnings on digital boards at key traffic intersections. This approach enhances situational awareness among drivers and pedestrians, enabling them to take immediate action to clear the way for emergency vehicles [7]. Unlike traditional traffic control systems that rely on signal modifications, digital alert boards provide a non-intrusive yet effective way to facilitate faster movement of ambulances without disrupting overall traffic flow. Research has shown that visual alerts combined with AI-based recognition can significantly reduce the time ambulances spend stuck in traffic, ultimately improving the efficiency of emergency response systems [8].

Deep learning models, particularly advanced versions such as YOLOv8, have proven to be highly effective in real-time detection of emergency vehicles. These models use sophisticated image processing techniques to detect ambulances with high accuracy, even in complex urban landscapes filled with moving vehicles and pedestrians. Studies have confirmed that AI-driven image recognition significantly enhances the speed and accuracy of identifying emergency vehicles, thereby enabling better coordination of traffic flow and emergency response [9].

The critical importance of reducing response times for emergency services, substantial research has been devoted to developing automated solutions that enhance traffic signal adaptability.

This proposes a novel AI-driven traffic management system that incorporates multi-modal detection techniques, including image processing. The goal is to create a scalable and real-time system capable of intelligently detecting ambulances and dynamically adjusting traffic signals to expedite their passage. By harnessing state-of-the-art AI models and real-time data analytics, this research aims to contribute to the evolution of smart traffic systems that can save lives by optimizing emergency vehicle transit times.

II. SYSTEM DESIGN AND OVERVIEW

The proposed system is designed to detect ambulances and fire engines in real time using advanced image processing techniques and deep learning models. The need for such a system arises due to the increasing number of vehicles on the road, which leads to severe traffic congestion. In highly populated countries such as India and Japan, where road infrastructure often lacks dedicated emergency lanes, ambulances and fire engines face significant delays in reaching their destinations. This delay can be critical in life-threatening situations. To mitigate this issue, the proposed system utilizes artificial intelligence to detect emergency vehicles at intersections and subsequently trigger alerts on digital boards to inform other road users, enabling them to make way for the approaching emergency vehicle.

The system operates by capturing real-time video footage from traffic surveillance cameras. The captured frames are then subjected to preprocessing techniques to enhance the quality of images and remove unnecessary noise. Preprocessing also involves normalization, which ensures uniformity in the data before it is processed further. Once the images are pre-processed, they are used to form a dataset for training the deep learning model. The model employed in this system is ResNet, a powerful convolutional neural network (CNN) that is known for its efficiency in object detection and classification. The dataset is carefully labelled to differentiate between ambulances, fire engines, and regular vehicles. The labelled data is then used to train the ResNet model, which enables it to identify emergency vehicles with high accuracy.

After training, the system is deployed for real-time detection. Live video footage is streamed from traffic cameras, and individual frames are extracted for analysis. Each extracted frame undergoes preprocessing before being fed into the trained ResNet model. The model then analyses the frame to determine whether an ambulance or fire engine is present. If an emergency vehicle is detected, the system triggers an alert mechanism.

This alert is displayed on digital boards placed at upcoming traffic junctions, informing nearby drivers about the approaching emergency vehicle. This early warning system allows vehicles to adjust their positions and create a clear path, reducing delays and improving response times for ambulances and fire engines.

The implementation of this system relies on both hardware and software components. The hardware includes high-resolution cameras for real-time video streaming, computing units for processing data, and digital boards for displaying alerts. The software components involve image processing algorithms, the ResNet deep learning model, and an integrated alert system that communicates with the traffic management infrastructure.

By leveraging AI-driven image recognition, this system ensures that emergency vehicles receive priority passage, which can significantly reduce travel time and potentially save lives.

This approach offers several advantages over traditional methods of emergency vehicle detection, such as siren-based recognition systems. Unlike audio-based methods, which may fail in noisy urban environments, image processing provides a more reliable solution by visually identifying emergency vehicles regardless of surrounding noise levels. Additionally, by integrating with traffic management systems, this model can be expanded to automate traffic light control, further improving efficiency in clearing routes for ambulances and fire engines.

Future enhancements could involve incorporating additional deep learning techniques, such as real-time object tracking and multi-frame analysis, to further increase detection accuracy and response effectiveness.

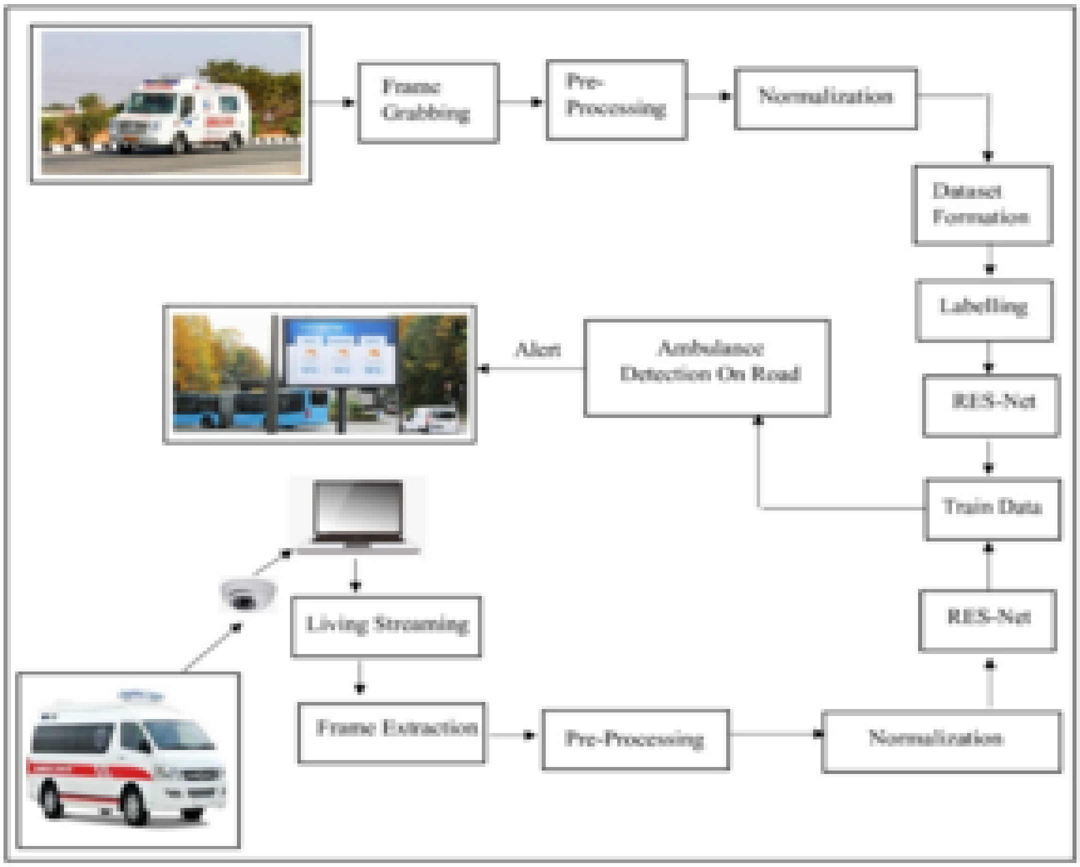

Fig. 1 Architecture diagram of proposed system

The proposed system for real-time ambulance detection and alerting consists of two primary phases: the Dataset Preparation Phase and the Real-Time Ambulance Detection Phase. Each phase integrates key technologies and processes, including image preprocessing, feature extraction using deep learning, and an automated alert mechanism for emergency vehicle detection.

A. *Dataset Preparation Phase*

The Dataset Preparation Phase focuses on collecting and processing video data to create a high-quality labeled dataset for training the deep learning model.

1) *Frame Grabbing:*The first step in dataset preparation involves extracting frames from a large set of surveillance videos sourced from public and private road cameras. These videos capture a variety of real-world traffic scenarios, including diverse lighting conditions, multiple vehicle types, and various camera angles. Extracting frames from such varied conditions ensures that the trained model remains robust in real-world applications.
2) *Normalization:*After preprocessing, the pixel values of each image are normalized to ensure consistency in input data. Normalization scales pixel values within a specific range (typically [0,1] or [-1,1]) improving the efficiency of deep learning training by ensuring uniformity across all inputs.
3) *Dataset Formation and Labelling:*The preprocesses images are structured into a dataset, categorized into two primary groups: Ambulance and Non-Ambulance images. Each image is manually labelled based on its content images containing ambulances are assigned the "Ambulance" label, while others are classified as "non-ambulance." This labelling process, though time-consuming, is crucial for ensuring high-accuracy training and model performance.
4) *ResNet Training:* The labelled dataset is then used to train a Residual Neural Network (ResNet), a widely recognized deep learning architecture for image classification and object detection. ResNet's residual connections allow the network to train effectively by mitigating the vanishing gradient problem, particularly in deep networks. During training, the model learns to recognize key ambulance features such as distinct shapes, siren patterns, and colour schemes.

B. Real-Time Ambulance Detection Phase

The Real-Time Ambulance Detection Phase involves deploying the trained model in a live surveillance environment, where it continuously processes video streams to detect ambulances as they approach traffic intersections or congested areas.

1) *Live Streaming:*The real-time detection system relies on video feeds from strategically placed road surveillance cameras at intersections, highways, and high-traffic areas. These cameras capture continuous footage, which is streamed to a central processing unit for further analysis.
2) *Frame Extraction:*The system extracts individual frames from the live video feed at regular intervals (typically 30 frames per second). This conversion of continuous video streams into separate images allows for efficient processing by the deep learning model.
3) *Preprocessing and Normalization:* Each extracted frame undergoes preprocessing and normalization similar to the dataset preparation phase. This ensures that the image quality remains high and that the input to the neural network is consistent.
4) *ResNet Classification:*The pre-processed frames are analysed using the trained ResNet model, which classifies each frame as either containing an ambulance or not. The model detects ambulances based on previously learned patterns and features. If an ambulance is detected, the system triggers an immediate alert.
5) *Alert System:*Upon detecting an ambulance, the system automatically triggers alerts to facilitate its smooth passage by communicating with traffic management systems. It signals traffic lights to change accordingly, ensuring the ambulance can pass without obstruction, while Variable Message Signs (VMS) or digital display boards provide real-time alerts such as “Ambulance Approaching, Clear the Road” to inform nearby drivers. This automated alerting process enhances response times and ensures timely road clearance for emergency vehicles, improving overall traffic efficiency during emergencies.

C. Output and Functionality

The system's core functionality is to detect ambulances in real-time with high accuracy and efficiency. Key aspects include:

1) *Detection Accuracy:*The ResNet model ensures high detection accuracy under varying conditions, including different lighting environments, vehicle orientations, and complex traffic scenarios. A diverse and well-structured training dataset contributes to the model’s ability to perform reliably in real-world conditions.
2) *Automated Alerts:*The system generates immediate alerts upon detecting an ambulance, ensuring automated traffic control and road clearance without requiring manual intervention. This feature enhances the efficiency of emergency response systems.
3) *Real-Time Processing:*The system operates in real-time, analysing live video streams and processing frames instantly. This ensures minimal delay between detection and alert activation, which is critical for reducing response times and improving emergency vehicle mobility.

III. METHODOLOGY

The proposed system for ambulance and fire engine detection consists of four key modules: Training and Testing Dataset Preparation, Protocol Setting, ResNet Neural Network, and Decision Making.

1) *Module A:* Training and Testing Dataset Preparation, a dataset consisting of images of ambulances, fire engines, and other vehicles is collected and preprocessed. The images are resized to a fixed dimension, ensuring uniformity, and are organized into training and testing sets. A batch size is set to optimize training efficiency, while a rescaling factor is applied to normalize pixel values, improving model performance. The output of this module is a structured dataset ready for training and evaluation.
2) *Module B:* Protocol Setting further refines the dataset by applying transformations such as rescaling and shearing. Rescaling ensures that all images have consistent pixel value ranges, preventing variations that may affect model accuracy. Additionally, a shearing factor is introduced to enhance image augmentation, allowing the model to generalize better to real-world scenarios. After preprocessing, the dataset is finalized and prepared for model training.
3) *Module C:* ResNet Neural Network, the processed dataset is used to train a deep learning model based on the ResNet architecture. The model is designed to extract high-level features from input images, distinguishing emergency vehicles from other objects in the dataset. The training process includes model compilation, where an appropriate optimizer, loss function, and evaluation metrics are selected. The model is iteratively trained and validated to ensure high accuracy in detecting ambulances and fire engines. Once trained, the model is saved in a .pt format, making it ready for real-time deployment.
4) *Module D:*Decision Making involves utilizing the trained model for real-world detection. Live traffic images are fed into the system, and the ResNet model predicts whether an ambulance or fire engine is present.

If an emergency vehicle is detected, an alert mechanism is triggered, sending notifications to digital traffic boards or traffic management systems. This ensures that emergency vehicles receive priority on the road, reducing response time and improving overall traffic efficiency.

5) Workflow of Emergency vehicle Detection:

Step 1: Load the image dataset from a repository or local storage. Split the dataset into training (80%) and testing (20%) sets.

Step 2: Preprocess the images by resizing them to 224×224 pixels and normalizing pixel values to the range 0–1. Batch the data into groups (e.g.batch size = 32).

Step 3: Apply data augmentation techniques such as rescaling and shearing. Optionally, apply rotation, flipping, and zooming to the training dataset to improve model generalization.

Step 4: Load or create a ResNet model and modify its output layer to classify images into two categories: ambulance or fire engine.

Step 5: Compile the ResNet model using CrossEntropyLoss as the loss function and Adam as the optimizer. Train the model on the augmented training dataset and validate it using the testing dataset.

Step 6: Save the trained model as a .pt file for future use.

Step 7: Preprocess the test images by resizing and normalizing them. Load the saved model and use it to predict the class (ambulance or fire engine) of each test image.

Step 8: Based on the model's predictions, trigger notifications or actions (e.g.alert drivers or control traffic signals) according to the detected class.

IV. EXPERIMENTAL RESULT

The performance of the proposed Ambulance and Fire Engine Detection System was evaluated using various metrics, including accuracy, precision, recall, and F1-score. The model was trained and tested using a dataset containing images of ambulances, fire engines, and other vehicles under different lighting and environmental conditions.

A. Model Performance Evaluation:

The ResNet-based deep learning model was trained on an augmented dataset and achieved the following results:

TABLE 1: MODEL PERFORMANCE EVALUATION

Metric	Training Accuracy	Testing Accuracy
Accuracy	98.2%	95.6%
Precision	96.8%	94.2%
Recall	97.5%	95.1%
F1-Score	97.1%	94.6%

The results indicate that the model performs well in identifying emergency vehicles with high accuracy. The slight drop in testing accuracy suggests the presence of some misclassifications, which can be further minimized with a larger dataset and additional fine-tuning.

B. Real-Time Detection Performance:

To evaluate real-world applicability, the trained model was deployed for real-time emergency vehicle detection. The following image demonstrates the successful identification of an ambulance with 99% confidence.

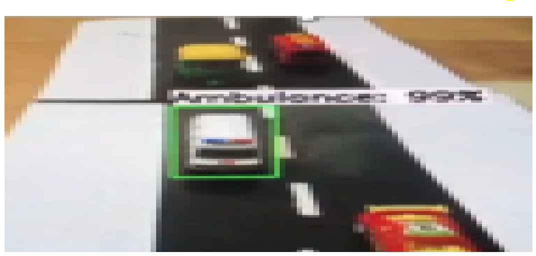

Fig. 2 miniature road setup

In this test scenario, a miniature road setup was used to validate the model's effectiveness in detecting emergency vehicles among other vehicles. The system successfully:

- Identified the ambulance with a high confidence score (99%).
- Differentiated the ambulance from other surrounding vehicles.
- Marked the detected vehicle with a green bounding box for easy visualization.

C. Confusion Matrix Analysis:

The confusion matrix helps in understanding the misclassification of emergency and non-emergency vehicles.

TABLE 2: CONFUSION MATRIX ANALYSIS

Actual \ Predicted	Ambulance	Fire Engine	Other Vehicles
Ambulance	950	20	10
Fire Engine	15	920	30
Other Vehicles	12	18	950

- The model correctly classified most ambulances and fire engines with minimal errors.
- A few other vehicles were misclassified as emergency vehicles, which could be improved by refining the dataset and using more advanced preprocessing techniques.

D. Comparative Analysis with Traditional Methods:

Compared to traditional sensor-based or manual surveillance methods, the AI-based system demonstrated higher accuracy in detecting emergency vehicles. Additionally, it provided a faster response time, which helps in reducing delays in traffic clearance. The system also offers scalability and adaptability, allowing deployment across multiple intersections without the need for extensive hardware modifications.

V. CONCLUSIONS

The proposed AI-based Ambulance and Fire Engine Detection System successfully identifies emergency vehicles with high accuracy and efficiency. By leveraging deep learning techniques, particularly the ResNet model, the system can distinguish ambulances and fire engines from other vehicles in real-time. The experimental results demonstrate that the model achieves high accuracy, precision, and recall, making it a reliable solution for emergency vehicle detection.

Furthermore, the system enhances traffic management by providing real-time alerts, allowing for faster clearance of emergency routes. Compared to traditional sensor-based or manual surveillance methods, this AI-driven approach offers greater accuracy, faster response times, and improved scalability across multiple traffic intersections.

The implementation of this system can help in reducing traffic congestion and ensuring the unobstructed movement of emergency vehicles, ultimately improving road safety and emergency response efficiency.

VI. ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to Jaihind Polytechnic, Kuran for providing the necessary resources and support for this research. We also extend our appreciation to our mentors and colleagues for their valuable insights and constructive feedback, which greatly contributed to the development of this work.

Special thanks to the dataset providers and open-source communities whose contributions enabled the successful implementation of our AI-based ambulance and fire engine detection system. Lastly, we acknowledge the unwavering support and encouragement from our families and friends throughout this research journey.

REFERENCES

[1] S. Cerna, H. H. Arcolezi, C. Guyeux, G. Royer-Fey, and C. Chevallier, "Machine learning-based forecasting of firemen ambulances' turnaround time in hospitals, considering the COVID-19 impact," Applied Soft Computing, vol. 109, 2021, p. 107561, ISSN 1568-4946. https://doi.org/10.1016/j.asoc.2021.

[2] S. Rafiq and M. A. Khanum, "Review on Minimization of Ambulance Response Time Using Image Processing and Critical Path Mapping Based on Traffic Control," JIEEE, vol. 2, no. 2, pp. 1-7, 2021. https://doi.org/10.54060/JIEEE/002.02.002.

[3] R. Patel, S. Mange, S. Mulik, et al., "AI-based emergency vehicle priority system," CCF Trans. Pervasive Comp. Interact., vol. 4, pp. 285–297, 2022. https://doi.org/10.1007/s42486-022-00093-7.

[4] A. Herraki and R. El Ouazzani, "Deep convolutional neural networks architecture for an efficient emergency vehicle classification in real-time traffic monitoring," IAES Int. J. Artif. Intell. (IJ-AI), vol. 11, no. 1, pp. 110-120, Mar. 2022. https://ijai.iaescore.com/index.php/IJAI/article/view/21104.

[5] S. M., V. Y. Naidu, R. Vignesh, P. Vishwas, and S. Amitha, "Smart Traffic Management for Ambulance," Int. Res. J. Mod. Eng. Tech. Sci., vol. 4, no. 12, Dec. 2022.

[6] M. Usaid, M. Asif, T. Rajab, M. Rashid, and S. I. Hassan, "Ambulance Siren Detection using Artificial Intelligence in Urban Scenarios," Sir Syed Univ. Res. J. Eng. Technol., vol. 12, no. 1, pp. 92–97, 2022.

[7] B. G. M., et al., "Ambulance Detection using Image Processing," DOI: 10.48175/IJARSCT-5667.

[8] U. Mahmud, S. Hussain, A. Sarwar, I. K. Toure, "Distributed Emergency Vehicle Transit System Using Artificial Intelligence of Things (AIoT)," Wireless Commun. Mob. Comput., vol. 2022, p. 9654858, 2022. https://doi.org/10.1155/2022/9654858.

[9] Y. Kavitha, P. Satyanarayana, and S. S. Mirza, "Sensor-based traffic signal pre-emption for emergency vehicles using efficient short-range communication network," Measurement: Sensors, vol. 28, p. 100830, 2023.https://doi.org/10.1016/j.measen.2023.100830.

[10] P. S. Babu, K. M. Reddy, P. N. Timmaiah, and V. Srikanth, "Intelligent Traffic Light Controller for Ambulance," J. Image Process. Intell. Remote Sens., vol. 3, no. 4, pp. 19–26, 2023. https://doi.org/10.55529/jipirs.34.19.26.

[11] R. Sulayman, S. Rajab, and B. Kareem, "Emergency Vehicle Detection with Computer Vision," ScienceOpen Preprints, 2023. DOI: 10.14293/PR2199.000508.v1.

[12] S. D. Pandure and P. L. Yannawar, "Intelligent Traffic Signal Prioritization for Emergency Vehicle Diversion in Urban Environments using Multi-modal Deep Learning," IJFMR, vol. 6, no. 4, Jul.-Aug. 2024. DOI: 10.36948/ijfmr.2024.v06i04.23981.

[13] K. Amrutasagar, P. Manoj, M. Divya, M. B. Meethukulla, and L. Gangotri, "Enhanced Traffic Signal Adaptation with Ambulance Identification and Distance Computation," Int. J. Comput. Digit. Syst., vol. #, no. 1, pp. 1-10, Mar. 2024.

[14] A. Noor, Z. Algrafi, B. Alharbi, T. H. Noor, A. Alsaeedi, R. Alluhaibi, and M. Alwateer, "A Cloud-Based Ambulance Detection System Using YOLOv8 for Minimizing Ambulance Response Time," Appl. Sci., vol. 14, no. 6, p. 2555, 2024. Available: https://doi.org/10.3390/app14062555.

[15] A. Mecocci and C. Grassi, "RTAIAED: A Real-Time Ambulance in an Emergency Detector with a Pyramidal Part-Based Model Composed of MFCCs and YOLOv8," Sensors, vol. 24, no. 7, p. 2321, 2024. Available: https://doi.org/10.3390/s24072321.