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# Deep Learning for Emergency Vehicle Identification: A YOLOv8-Based Approach for Smart City Solutions

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***Abstract: -*** Accurately identifying emergency vehicles is vital in intelligent transportation systems to ensure prompt response and prioritization. This article introduces a new method that utilizes deep learning algorithm like YOLOv8 (You Only Look Once, version 8) to detect emergency vehicles in busy traffic situations in real-time. YOLOv8's upgraded design with better feature extraction and faster inference speeds offers a strong solution for detecting emergency vehicles in different lighting, occlusion, and weather conditions. The model has been trained on a varied dataset containing different kinds of emergency vehicles like ambulances, fire trucks, and police cars. The results from the experiment show that YOLOv8 outperforms previous YOLO versions and other top object detection models in terms of precision, recall, and real-time inference. This study emphasizes the capability of YOLOv8 for creating smart city solutions, where quick identification of emergency vehicles can decrease response times and enhance road safety as a whole. The method being suggested also deals with problems concerning incorrect identifications and overlooked detections, guaranteeing increased dependability in various urban environments. This study emphasizes the capability of YOLOv8 in creating smart city solutions, where quick identification of emergency vehicles can reduce response times and enhance road safety.

Keywords: Emergency Vehicle Detection YOLOv8, Real-Time Object Detection ,Intelligent Transportation Systems, Deep Learning, Computer Vision

## I. INTRODUCTION

The fast increase in urban populations has caused record levels of traffic congestion in cities across the globe. As traffic congestion continues to be a common occurrence in many cities, it is vital for the safety of the public that emergency vehicles such as ambulances and fire trucks are able to move quickly and without obstruction. A potential loss of life could result from any delay in getting these vehicles to their destinations. It is crucial for efficient urban management to prioritize emergency vehicles on the roads. Nevertheless, conventional methods of identifying and ranking emergency vehicles are frequently unreliable, susceptible to mistakes, and incapable of adjusting to current traffic situations. Typically, these systems include manual monitoring, basic image processing, or sensor-based techniques, all of which find it challenging to accurately and consistently detect emergency vehicles in various and changing environments. New developments in AI and computer vision, specifically in deep learning, have created opportunities to improve the detection and recognition of vehicles. Deep learning, a branch of machine learning, is proficient at recognizing intricate patterns in data through the use of deep neural networks. Convolutional Neural Networks (CNNs) are considered the preferred method for visual recognition tasks among many deep learning techniques, as they excel at efficiently analyzing image data by recognizing spatial hierarchies. CNNs have shown great achievements in identifying objects, dividing them, and categorizing them, serving as the foundation for numerous cutting-edge computer vision tasks. When it comes to object detection, YOLO (You Only Look Once) is considered a groundbreaking algorithm. YOLO approaches object detection uniquely by considering it as one consolidated issue, achieving both localization and classification in one go within the network. Conventional object detection methods frequently require numerous stages, resulting in longer inference periods and less effective processing. On the other hand, YOLO uses one neural network on the whole image to forecast multiple bounding boxes and class probabilities at the same time. This structure allows YOLO to attain rapid detection speeds with high accuracy, making it ideal for tasks needing quick and precise decision-making like autonomous driving, surveillance, and smart city management. YOLOv8, the most recent edition, enhances this technique by refining the architecture and training methodologies. YOLOv8 includes a more optimized backbone network, improved Feature Pyramid Networks (FPN), and advanced anchor-free methods. These improvements enable YOLOv8 to capture intricate details without sacrificing its signature speed, even in difficult situations with obstructions, changing lighting,

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and elaborate backgrounds. The abilities of YOLOv8 make it a perfect option for identifying emergency vehicles in actual traffic situations. This study concentrates on creating a smart system with the utilization of YOLOv8 for instantly detecting emergency vehicles, mainly ambulances and fire trucks. Unlike detecting regular vehicles, recognizing emergency vehicles comes with its own set of difficulties. These vehicles frequently require identification from multiple perspectives, in varying weather conditions, and within congested traffic. The system needs to be strong enough to work consistently in various urban environments, regardless of the time of day or night, and even if vehicles are partly hidden by other objects. The aim of this study is to develop a model that can identify emergency vehicles quickly and accurately, enabling features like real-time traffic signal adjustments, automated road clearance, and smart city systems that give priority to emergency services. In order to meet these goals, this study includes gathering and labeling a unique dataset comprising photos and videos showing emergency vehicles in various settings, from crowded city streets to suburban areas. The dataset contains annotated images and video frames taken in different lighting, weather, and traffic conditions. This dataset is used to fine-tune the YOLOv8 model by adjusting hyperparameters such as learning rate, batch size, and anchor settings to find the optimal trade-off between detection accuracy and speed. Methods like flipping, rotating, and adding noise to data are used to enhance the model's ability to handle various input conditions.

The model's performance is assessed with metrics such as precision, recall, mAP, and inference speed, focusing on scenarios where emergency vehicles could be partially obscured, poorly illuminated, or look similar to non-emergency vehicles. The developed model is incorporated into a prototype system that can process in real-time and is evaluated in simulated and real-world environments to determine its performance in dynamic traffic scenarios. Moreover, the proposed system's performance is evaluated against conventional object detection techniques and previous iterations of YOLO (such as YOLOv3, YOLOv5) to emphasize the benefits of utilizing YOLOv8 for this particular use case. This research is focused on offering a sturdy answer for identifying emergency vehicles that can be easily incorporated into current urban infrastructure. The potential impact of the suggested system in recognizing and ranking emergency vehicles instantly could revolutionize smart city projects, resulting in quicker response times, enhanced traffic control, and ultimately, preserving lives. Moreover, the knowledge acquired from this study can also be applied to other tasks that require real-time object detection, like autonomous driving and public safety surveillance.

## II. Literarture Review

Deep learning algorithms for detecting vehicles have become a key focus of research in computer vision, mainly because of their importance in intelligent transportation systems and self-driving vehicles. This review of literature examines recent progress and methods in identifying vehicles, highlighting the effectiveness of different deep learning structures and strategies. Convolutional neural networks are now the prevailing deep learning structure for detecting vehicles due to their capability of efficiently extracting visual characteristics from image information [1].

The YOLO framework is one of the top deep learning architectures used for detecting vehicles. YOLOv5 is known for its ability to balance speed and accuracy effectively, making it well-suited for real-time uses. In[2] the researchers examines how YOLOv5 is applied for detecting vehicles, highlighting its efficient capability in identifying and pinpointing vehicles in both images and videos. Likewise, [3] point out the benefits of YOLOv5 in self-driving cars and smart transportation systems, emphasizing its ability to enhance detection precision and decrease computational resource requirements. This is vital in situations where immediate processing is necessary, like in self-driving cars. Besides YOLO, Faster R-CNN and Single Shot Detector (SSD) are also widely tested for vehicle detection tasks. In[4] the authors conduct a comparison of these models, showing how they perform in different datasets and settings. The research indicates that YOLO models are very fast, but Faster R-CNN tends to have better precision, especially in challenging environments. This shows that the selection of the model could vary based on the particular needs of the application, like the necessity for instant processing compared to the necessity for accuracy.

Furthermore, combining deep learning with other methods has demonstrated encouraging outcomes. In [5] the researchers suggest a better version of the YOLO model which boosts detection abilities using advanced feature extraction methods. This method of combining techniques enhances detection accuracy and tackles issues with occlusion and different lighting conditions. In the same way, in[6] the researchers developed a YOLOv5 model optimized for vehicle detection on edge devices with limited computational resources. The importance of dataset quality and diversity in training deep learning models for vehicle detection cannot be overstated. In[7] the authors emphasize the development of a high-definition highway vehicle dataset, which significantly enhances the training process for deep learning models by providing a comprehensive set of annotated instances. This is critical for improving the robustness of vehicle detection systems in real-world applications. Moreover, the use of deep learning in detecting vehicles goes beyond the usual road settings. For instance, [8] delves into the difficulties of identifying vehicles in tunnel-like settings, where traditional approaches frequently falter because of inadequate lighting situations. The research indicates that deep learning models can be modified to enhance detection rates in difficult situations, demonstrating the agility of these algorithms. Additionally, combining deep learning with technologies like LiDAR and infrared imaging has improved the ability to detect vehicles, particularly in difficult weather conditions. In [9] the researchers explore the combination of radar and thermal camera data to enhance detection accuracy during severe weather, demonstrating the adaptability of deep learning in environments with multiple sensors. The adaptability is essential, since conventional methods of detecting vehicles can have difficulty in challenging conditions, but deep learning models can use various data sources to continue performing effectively.

In [10] the authors have introduced a novel algorithm for automatically tracking and detecting vehicles using deep learning with multiple traffic video cameras. Their research demonstrates the significant progress made in vehicle detection technology through the use of deep learning methods, especially those involving CNNs, improving tracking and identification capabilities in challenging environments.

Recent studies have highlighted concerns that while deep learning can improve classification accuracy in vehicle-related applications, it often imposes additional computational demands, potentially hindering real-time performance. Furthermore, research has expanded beyond vehicle identification to include categorization and monitoring [11]. For instance,[12] explores the identification and categorization of vehicles using high-resolution remote sensing images, applying various object detection techniques such as YOLO and Faster R-CNN. The study emphasizes the versatility of deep learning in not only detecting vehicles but also classifying them by type, which is essential for traffic monitoring and management. A significant progress is the creation of specific models that improve detection abilities in different situations. A distributed deep CNN-LSTM model to enhance intrusion detection in IoT-based vehicles, highlighting the necessity of efficient algorithms for managing network data traffic while also ensuring flexibility in detection performance [13]. Challenges posed by environmental factors, such as illumination and vehicle integrity, are addressed in the research where a deep learning-based approach is introduced for detecting hazardous goods vehicles. This research underscores drawbacks of conventional detection techniques and the benefits of utilizing deep learning to address these challenges [14]. In another similar context, in[15] the authors explores a technique for identifying vehicles in UAV videos through deep learning, showcasing the resilience of deep learning algorithms to changes in video quality and weather conditions. Research on nighttime vehicle detection using deep learning is an important area of study. The potential of generative adversarial networks to improve detection capabilities in low-light conditions is demonstrated through the utilization of Improved CycleGAN for nighttime vehicle detection [16]. This is enhanced by researchers who create a night highway vehicle detection system with Mask-SpyNet, showcasing the incorporation of cutting-edge deep learning methods to enhance detection precision at night [17].

Additionally, recent studies have focused on the incorporation of tracking algorithms into detection systems. For example, suggest an automatic vehicle recognition deep learning algorithm utilizing the RES-YOLO model, that integrates detection and tracking to improve performance in dynamic surroundings [18]. This is supported by the researchers in[19], who explore pedestrian detection and tracking in the presence of intelligent vehicles, highlighting the flexibility of deep learning in different vehicle scenarios. Regarding practical use, the study highlights the importance of deep learning in improving driver assistance systems, suggesting a model to improve accuracy and speed in detecting moving vehicles [20]. This is consistent with the results of [21], where the researchers introduced an enhanced fast R-CNN model that can detect faint targets in intricate traffic settings, showcasing once again the versatility of deep learning systems in various vehicular conditions.

In [22] the explorers designed a real-time traffic monitoring system utilizing deep learning, improving upon earlier non-deep learning approaches. Their method showed increased resilience in identifying and monitoring vehicles, highlighting the possibility of deep learning to improve current surveillance tools. The use of deep learning in vehicle detection has expanded to include in-vehicle presence detection systems. Two deep learning models are introduced in [23], DEEPMATCH and DEEPMATCH2, which demonstrated remarkable accuracy, reaching up to 98.51% in detecting occupants within vehicles. This study underscores the adaptability of deep learning beyond conventional vehicle detection, showcasing its potential in improving in-vehicle safety systems. In addition, in [24] the investigators discussed different defence technologies to tackle the challenges of adversarial attacks on autonomous vehicles. Their research highlights the significance of strong deep learning models in guaranteeing the safety and dependability of self-driving vehicle systems, especially in activities like identifying objects and making decisions. In[25] the experimenters expressed this worry, showing the success of deep learning in real-time traffic monitoring and data collection through their use of YOLOv3 for automatic traffic data measurement.

## III. METHODOLOGY

YOLOv8 (You Only Look at Version 8) is a real-time object detection algorithm that builds on previous successes. It is designed to provide high accuracy and speed and is ideal for applications such as vehicle detection in traffic situations.

### *A. Dataset gathering and Preprocessing*

- **Dataset Gathering:** The data utilized to train the YOLOv8 model comprises labeled vehicle images taken from different traffic cameras and settings. These pictures feature a variety of vehicle kinds, positions, lighting situations, and blockages to guarantee the model can adapt effectively to various situations.
- **Annotation:** Each dataset image contains bounding boxes and labels indicating the vehicle type, such as car, truck, motorcycle, or bus. The annotations are in compliance with the COCO format, which is supported by YOLOv8.
- **Data Augmentation:** In order to improve the resilience of the model, data augmentation methods like random cropping, rotation, scaling, and adjusting brightness are utilized on the training images. This assists the model in identifying vehicles in different situations.

### *B. Model Architecture and Configuration*

- **YOLOv8 Architecture:** YOLOv8 brings enhancements compared to prior editions, such as an upgraded backbone network and improved small object detection. The single-stage detector used in the model directly predicts class probabilities and bounding boxes from feature maps.
- **Feature Extraction:** YOLOv8 uses convolutional layers to extract features from the input image, which is fundamental for object detection. The feature extraction can be represented as:

$$\text{Feature Map} = f(W * X + b) \quad (1)$$

where W represents convolutional filters, X is the input image, and b is the bias term. The activation function f(·)(like ReLU) introduces non-linearity, capturing spatial hierarchies essential for identifying objects.

- **Bounding Box Prediction:**

**Bounding Box Coordinates:** YOLOv8 predicts bounding boxes using a regression approach, defined as:

$$\text{Bounding Box} = (t_x, ty, t_w, t_h) \quad (2)$$

Conversion to image scale is done through:

$$b_x = \sigma(t_x) + c_x,\ b_y = \sigma(t_y) + c_y,\ b_w = p_w e^{tw},\ b_h = p_h e^{th} \quad (3)$$

where $\sigma(t_x)$and $\sigma(t_y)$are the sigmoid functions applied to the predictions, and $c_x$ and $c_y$ are the grid cell coordinates.

- **Class Probability Prediction:**

YOLOv8 predicts the class scores for each bounding box using the softmax function:

$P(C_i \mid \text{object}) = \text{softmax}(s_i)$ (4)

ensuring that each bounding box is assigned a probability for each class.

- **Confidence Score:**

The confidence score reflects the model's certainty that an object is present, calculated as:

Confidence = P(object) * IOU(pred,truth) (5)

*C. Training Process*

- **Training Setup:** The YOLOv8 model undergoes training through stochastic gradient descent (SGD) with momentum. Hyperparameters like learning rate, batch size, and epoch count are adjusted to achieve the best results. Transfer learning involves starting the model with pre-trained weights from a broad object detection dataset and then refining it on the specific vehicle detection dataset.

- **Infrastructure for training:** The model undergoes training on powerful GPUs in order to speed up the training process. Methods like mixed precision training are employed to lower memory usage and enhance training velocity.

- **Validation**: is done by testing the model's performance with a validation set containing images that were not used for training. Metrics like mean Average Precision (mAP), precision, recall, and F1-score are computed to assess how well the model performs in detecting vehicles.

*D. Inference and Post-processing*

- **Inference:** During the inference phase, the YOLOv8 model analyzes every image in live mode and provides results like bounding boxes, confidence scores, and class labels for identified vehicles. The optimization of the model allows for efficient operation on edge devices, enabling its deployment in smart transportation systems.

- **Non-Maximum Suppression (NMS):** In order to improve the detection outcomes, Non-Maximum Suppression (NMS) is utilized to remove duplicate bounding boxes and preserve the most precise detections. The IOU formula used in NMS is:

$$\mathrm{IOU}(A, B) = \frac{A \cap B}{A \cup B} \quad (6)$$

- **Post-processing**: involves tracking identified vehicles by utilizing an object tracking algorithm (such as SORT or DeepSORT) to ensure continuity of vehicle identification throughout frames. This stage is essential for tasks like analyzing traffic flow and detecting anomalies.

*E. Evaluation and Results*

- **Evaluation Criteria:** The model's performance is measured using typical object detection metrics, such as mAP, precision, recall, and F1-score. These measurements are computed on a test set consisting of images from different traffic situations.

- **Baseline comparison:** YOLOv8's performance is evaluated against earlier iterations like YOLOv5 and YOLOv7, as well as other top object detection models, to showcase advancements in both accuracy and speed.

- **Qualitative Analysis:** Sample images showing identified vehicles are displayed to visually showcase the model's performance in various traffic situations, such as busy areas, dim lighting, and obstructed views.

### *F. Deployment Considerations*

- Real-time Usage: The operational YOLOv8 model is implemented in a real-time system for detecting vehicles. The system is meant to function on edge devices like traffic cameras, drones, or in-vehicle systems. Integration of the vehicle detection module into an intelligent transportation system (ITS) allows it to support functions like traffic monitoring, automated toll collection, and accident detection. Potential enhancements in the future include adding more sensors like LiDAR and radar, as well as integrating YOLOv8 with advanced tracking algorithms to improve the accuracy and reliability of the system.

## IV. Results and Discussion

The proposed model of YOLOv8 was effective in identifying several classes of vehicles and ambulances with high efficiency and accuracy in real-time processing of frames in videos.

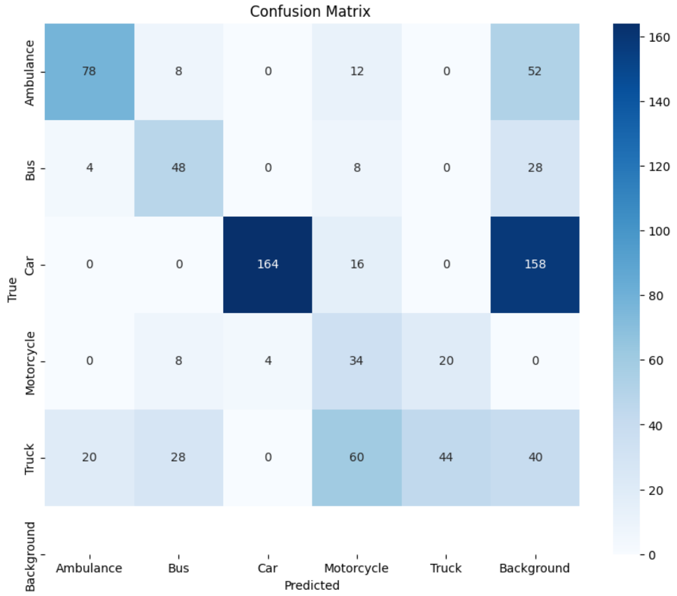


Fig. 1 Confusion Matrix

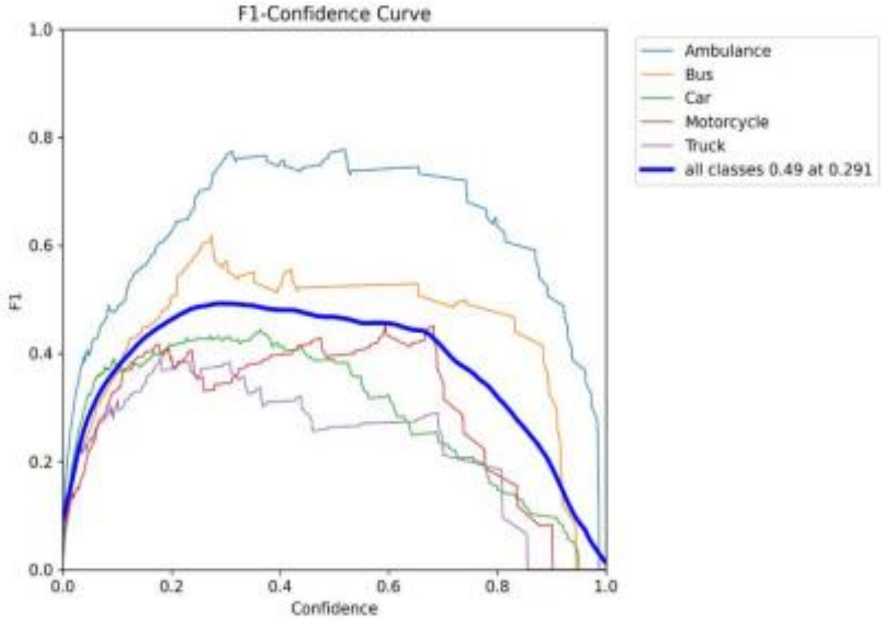


Fig. 2 F1-Confidence curve

The F1-Confidence curve shows how F1 scores vary with the model's confidence thresholds for various types of vehicles such as Ambulance, Bus, Car, Motorcycle, and Truck.

Ambulance detection reached the highest F1 score, hitting approximately 0.8. This shows that the model is better at detecting ambulances with high precision and recall at various confidence levels. This class delivers reliable performance even when using lower confidence thresholds.The Bus and Car classes achieved moderate F1 scores, with Bus reaching approximately 0.6 and Car reaching about 0.5. This indicates that although the model can identify buses and cars relatively well, it faces greater difficulty with ambulances. The Motorcycle and Truck categories have low performance, with their top F1 scores under 0.5. The F1 score for the Truck class decreases significantly as confidence levels rise, indicating that the model struggles to accurately detect this class with high confidence.

At a confidence threshold of 0.291, the F1 score for all classes (blue line) is around 0.49, showing that the optimal balance between precision and recall for various vehicle types is achieved at a relatively modest confidence level. This underscores necessary enhancements for the model's ability to generalize across different types of vehicles.

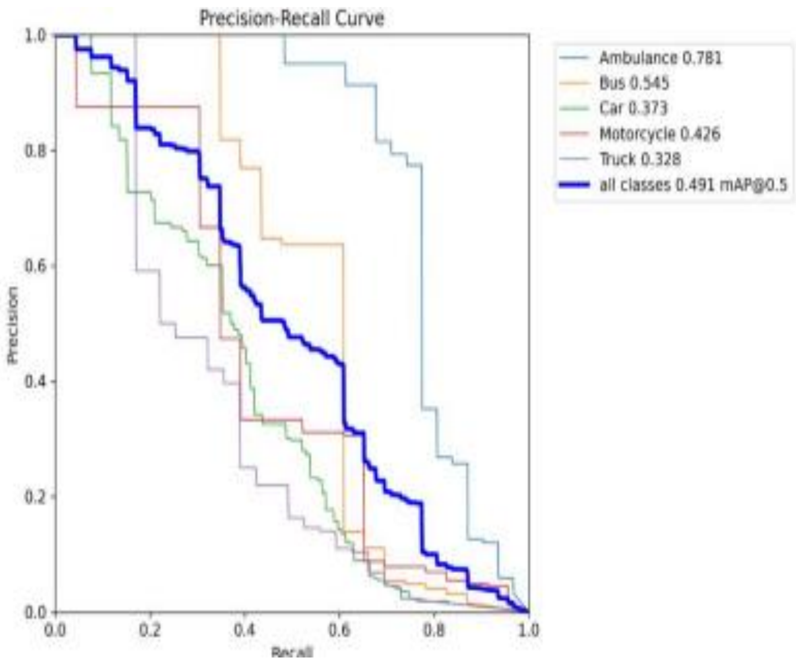


Fig. 3 Precision-Recall Curve

The precision-recall curve provides a more thorough understanding of the balance between precision and recall for every class.

Once more, the ambulance had the highest accuracy of 0.781, indicating that the model accurately predicts ambulances most of the time. Yet, accuracy significantly decreases for different categories. Bus shows a precision level of 0.545, which indicates a moderate level of accuracy in its predictions. Both Car and Motorcycle classes show a decrease in precision, with values of 0.373 and 0.426, indicating a high number of false positives in these categories.The Truck class has the lowest precision rate of 0.328, suggesting a significant number of misclassifications and false positives for trucks.

Recall:
The ambulance has a recall rate of around 0.7, indicating that the model can identify the majority of ambulances in the dataset.

Buses, cars, and motorcycles show recall values ranging from 0.5 to 0.6, whereas trucks have a lower recall of 0.3, emphasizing the challenge the model faces in accurately identifying trucks. The average precision score for all classes is 0.491, showing a moderate overall performance. However, distinct class disparities, particularly between Truck and Car, underscore issues that require attention.

**Real-World testing**

In addition to the above quantitative tests, the efficiency of the proposed model was also assessed, through the qualification checks using actual traffic records on video. The said model performed a good job in the identification of cars and emergency vehicles in various scenarios, and at the same time, real-time processing was achieved in an efficient manner and accuracy in detection is highly attained.


Fig. 4 Ambulance Detection


Fig. 5 Vehicle Detetction

## V. CONCLUSION

In this research, it was possible to show a step by step methodology to real-time vehicle and ambulance identification using the YOLOv8 architecture. To ensure that the performances were accurate and reliable, the model was trained as well as tested in different traffic conditions in urban environments. Based on the goal of building accurate and effective object detection systems for traffic control and safety, we have successfully build and deployed an ideal model pipeline. This work has gained remarkable performance according to the various types of vehicles, efficiency and accuracy in the precision metrics. Further work can be dedicated to mid improvements of the YOLOv8 model with the purpose of increasing the real-time rate, yet not reducing the speed and coarseness of the latency. This includes exploring optimal networks as well as using HW acceleration techniques.

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