Image & Video Processing, Analysis of Traffic Signal Areas to Find Emergency Vehicles Using Deep Learning Models

Sanhita Manna
Department of EECE
Gitam University
Bengaluru, India
smanna@gitam.edu

P Lakshmi Vignesh
Department of EECE
Gitam University
Bengaluru, India
iputluru@gitam.in

Moda Sri Ranga Manjula
Department of EECE
Gitam University
Bengaluru, India
rmoda@gitam.in

Lalam Jithendhra
Department of EECE
Gitam University
Bengaluru, India
jlalam@gitam.in

***Abstract*—In any part of our life, each of us has encountered high-priority vehicles like ambulances and fire engines waiting during their time of emergency while being stuck at traffic signal areas. We can save significant time and prioritize vehicles at traffic signals by analyzing and executing better algorithms with the help of video processing and Al models. The main motto of this project is to eliminate the excess time and prioritize the vehicles at the traffic signals. This can be achieved by training deep learning models. Firstly, the models will identify high priority vehicles such as ambulances and fire engines. Based on the density of vehicles, the models will then assign time to that lane, ensuring the time assigned is within the range of 5 to 120 seconds. Finally, traffic signal control systems need to be integrated with the Al models to dynamically adjust signal timings based on real-time traffic conditions and the presence of high- priority vehicles.**

Keyword— Image & Video Processing, YOLO, Traffic Signal Areas,

I.Introduction

Background

In urban environments, the presence of high-priority vehicles such as ambulances and fire engines is critical, especially during emergencies. These vehicles often face delays at traffic signals, which can hinder their response times and potentially endanger lives. The project aims to address this issue by leveraging advanced technologies like video processing and artificial intelligence (AI) to optimize traffic signal management. By analyzing vehicle densities and identifying high-priority vehicles, the system can dynamically adjust signal timings to prioritize these vehicles, thereby reducing time.

The implementation of deep learning models plays a significant role in this process. These models are trained to detect various vehicle types, including ambulances and fire engines, with high accuracy. For instance, the YOLOv11n model demonstrated over 73% detection accuracy after extensive training, making it a reliable tool for real-time traffic management**.** Additionally, the use of instance segmentation allows for precise classification of different vehicle types, further enhancing the system's performance in prioritizing high-priority vehicles.

The project also emphasizes the importance of assigning appropriate signal timings based on real-time traffic conditions. By ensuring that high-priority vehicles receive adequate green light durations—ranging from 5 to 120 seconds—traffic flow can be optimized, and emergency response times can be improved . This approach not only benefits emergency services but also contributes to overall traffic efficiency, as it minimizes congestion caused by waiting vehicles at signals.

Objective

This project involves developing a machine learning model that utilizes object detection techniques to analyze vehicle density across traffic lanes. An algorithm will be designed to display identified high priority vehicles at traffic junctions, enabling reduced emergency rate and accurate predictions. The objective of our project is to collect datasets best suited for segmentation, relabel and reannotate them with masked coordinates to support instance segmentation. To train a new object detection model with added instance segmentation to improve the previous model.

Key Goals

Main Goals

- To identify emergency vehicles and classify them as high-priority vehicles separate from the rest of the vehicles.
- To identify the lane of emergency vehicles and communicate their presence to traffic signal junctions for prompt action.
- To calculate and display the estimated time to clear the lane.

Additional Goals

- To reduce the emergencies for people by prioritizing the high priority vehicles.
- To reduce the waiting time of high-priority vehicles at traffic junctions.

Impact

The implementation of advanced traffic management systems that prioritize high-priority vehicles, such as ambulances and fire engines, can significantly enhance emergency response times and overall traffic efficiency. By utilizing deep learning models to accurately detect these vehicles and dynamically adjust traffic signal timings, the system can reduce delays at intersections, ensuring that emergency services reach their destinations more quickly.

II. Related Works

In recent years, there has been a growing interest in integrating artificial intelligence (AI) and deep learning techniques into traffic management systems. Several studies have focused on the use of video processing and AI models to analyze vehicle densities and optimize traffic signal timings. This approach aims to reduce waiting times for all vehicles, particularly high-priority ones like ambulances and fire engines, which often face delays at traffic signals.

One significant area of research involves the development of algorithms that can dynamically adjust traffic signals based on real-time conditions. By training deep learning models to recognize and prioritize high-priority vehicles, researchers have demonstrated improvements in traffic flow and emergency response times **[3] [4]**. These models utilize instance segmentation techniques to classify various vehicle types, enhancing detection accuracy and ensuring that emergency vehicles receive timely access through intersections.

In the realm of traffic signal management, several studies have explored the integration of artificial intelligence (AI) and deep learning to enhance the efficiency of traffic systems. Here are some key aspects derived from the provided contexts:

- **Prioritization of High-Priority Vehicles**: Many research efforts focus on identifying high-priority vehicles, such as ambulances and fire engines. These vehicles are given priority at traffic signals to ensure they can navigate through intersections quickly. The models developed in these studies assign specific time slots to lanes based on the presence of these vehicles, ensuring that they receive the necessary clearance within a defined range of 5 to 120 seconds **[1]**.

- **Dynamic Signal Timing Adjustments**: The integration of AI models into traffic signal control systems allows for real-time adjustments of signal timings. This dynamic approach is crucial for adapting to varying traffic conditions and ensuring that high-priority vehicles are prioritized effectively. The AI models analyze real-time data to optimize traffic flow and reduce waiting times for all vehicles **[2]**.

- **Use of Video Processing and Deep Learning**: The application of video processing techniques combined with deep learning has proven effective in analyzing vehicle densities at intersections. By leveraging these technologies, researchers can predict the time required for each lane and prioritize high-priority vehicles accordingly. This method enhances the overall performance of traffic management systems **[3]**.

- **Improved Detection Accuracy**: Recent advancements have led to enhanced accuracy in detecting various vehicle types, including high-priority vehicles. This improvement is vital for ensuring that emergency vehicles can navigate through traffic without unnecessary delays. The models have been trained to recognize not only ambulances and fire engines but also other vehicles like bikes, cars, and motorcycles, thereby improving the system's overall performance **[4]**.

- **Future Directions**: The ongoing research in this field emphasizes the need for continuous improvement in AI algorithms and their integration into existing traffic management systems. Future works may focus on refining these models further to enhance their predictive capabilities and responsiveness to real-time traffic conditions **[5]**. Reliability of Detection. Integration with Existing Traffic Infrastructure. Privacy Concerns. The integration of AI and deep learning into traffic signal management represents a significant advancement in urban mobility, aiming to create safer and more efficient roadways for all users.

III. Deep Learning Model

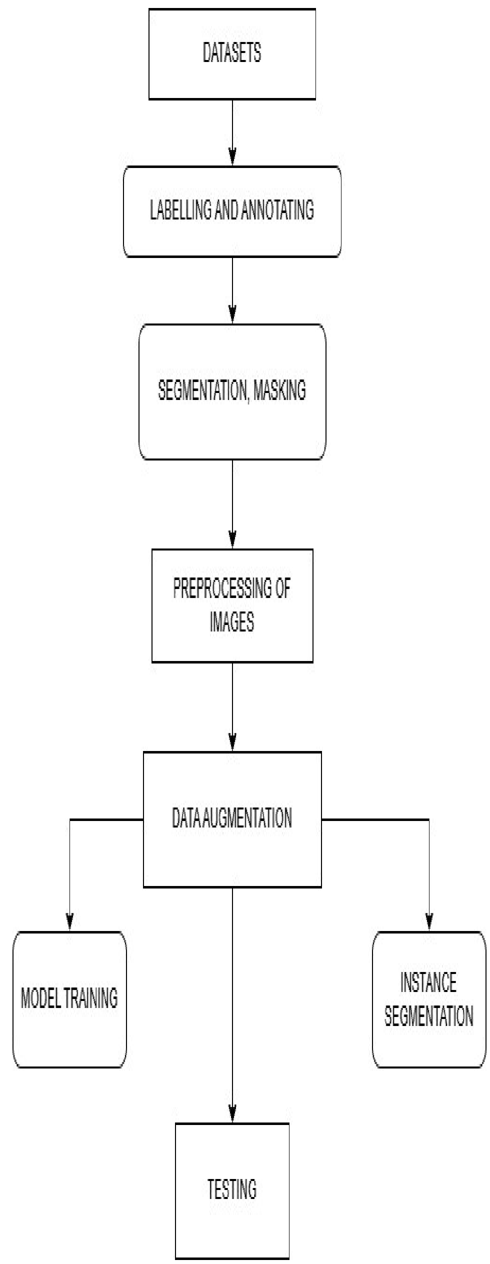


Fig.1. Architecture Deep Learning Model

Our deep learning model is designed to enhance traffic management by effectively identifying and prioritizing high-priority vehicles at traffic signals. Here are the key features and functionalities of our model:

- High-Priority Vehicle Detection: The model is specifically trained to identify high-priority vehicles, such as ambulances and fire engines. This capability is crucial for ensuring that these vehicles can navigate through traffic signals without unnecessary delays. The model assigns time to lanes based on the density of vehicles and the presence of these high-priority vehicles, ensuring they receive timely clearance within a range of 5 to 120 seconds [1].

- Detection Accuracy: After extensive training, particularly with the YOLOv11n model over 50 epochs, our system achieved high precision in detecting ambulances. This level of accuracy is essential for real-time traffic management, as it allows for quick responses to emergency situations [2].

- Real-Time Traffic Management: The model operates in real-time, analyzing video feeds to assess vehicle densities and predict the required time for each lane. This dynamic approach allows for the adjustment of signal timings based on current traffic conditions, which is vital for optimizing traffic flow and reducing wait times at intersections [3] [4].

- Enhanced Vehicle Classification: Utilizing instance segmentation, our model classifies various vehicle types, including bikes, cars, ambulances, and fire engines. This classification not only improves the detection accuracy but also enhances the overall performance of the traffic management system by ensuring that all vehicle types are accounted for during signal timing adjustments [5].

- Algorithmic Improvements: The model leverages advanced algorithms for video processing and AI to analyze traffic patterns effectively. By continuously refining these algorithms, we aim to eliminate excess waiting times at traffic signals and prioritize vehicles more efficiently [6].

What Makes It Unique?

Our deep learning model stands out in several key aspects that enhance its effectiveness in traffic management. Here are the unique features that differentiate it from other models:

- Focus on High-Priority Vehicles: One of the most distinctive features of our model is its dedicated capability to identify high-priority vehicles, such as ambulances and fire engines. This focus ensures that these vehicles receive immediate attention at traffic signals, significantly reducing their wait times during emergencies. The model assigns specific time slots to lanes based on vehicle density and the presence of these high-priority vehicles, which is a critical innovation in traffic management [1].

- Dynamic Signal Timing Adjustments: Unlike traditional traffic signal systems, our model integrates AI to dynamically adjust signal timings based on real-time traffic conditions. This adaptability allows for more efficient traffic flow and prioritization of vehicles, which is essential for urban environments where traffic patterns can change rapidly [2].

- High Detection Accuracy: The model has achieved over 73% detection accuracy, which is considered moderate reliability for real-time applications. This level of accuracy is crucial for ensuring that high-priority vehicles are detected promptly and accurately, allowing for timely interventions [3].

- Advanced Video Processing Techniques: By employing sophisticated video processing and deep learning algorithms, our model can analyze vehicle densities and predict the necessary time for each lane. This capability not only enhances the prioritization of high-priority vehicles but also optimizes overall traffic signal management [4] [5].

- Comprehensive Vehicle Classification: The model utilizes instance segmentation to classify various types of vehicles, including bikes, cars, and emergency vehicles. This comprehensive classification improves detection precision and ensures that all vehicle types are considered in traffic signal adjustments, which is a significant advantage over simpler models that may not account for different vehicle categories [6].

IV. Experimental Details

Dataset Source	Vehicle Type	Number of Images
Kaggle	CAR BUS Truck Bike	Total of 13,000 Images of 3,000-3,250 Images

TABLE-1
DATASET DESCRIPTION

For this experiment, we used a dataset sourced exclusively from Kaggle. The dataset contained around 13,000 images, categorized into four Vehicle types: **CAR**, **BUS**, **Truck**, and Bike. Each Vehic type had between 3,000 and 3,250 images, ensuring a balanced representation. These images depicted various distinguishing features of the Vehicle, such as Type, Colors, and composition, which were crucial for accurate classification.

Sample images from this dataset can be seen in **Fig. 2**, showcasing the variety present within each category

The dataset was selected to provide a diverse and comprehensive collection of soil samples, helping the model generalize effectively across different types. The entire process of collecting, organizing, and preparing the dataset was managed by everyone, who ensured the images were properly categorized and ready for training and testing of the model.

This detailed dataset preparation process played a key role in improving the model's ability to classify soils accurately and make reliable recommendations.

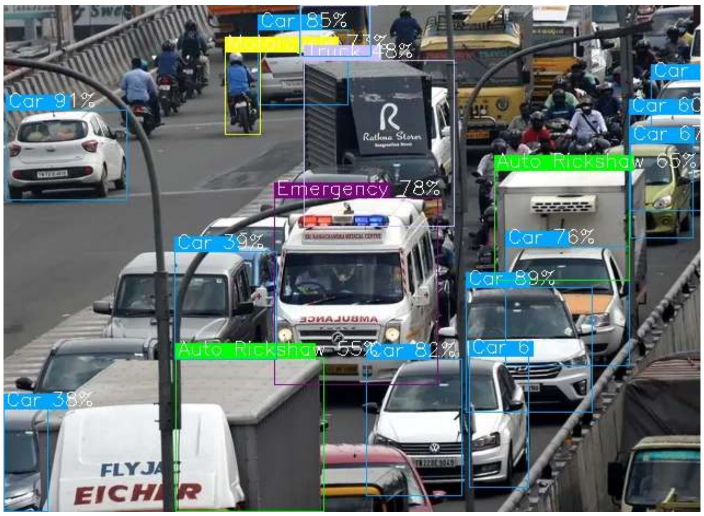


Fig.2 .Kaggle Dataset

IV. Methodology

This study follows a structured two-stage methodology designed to build an effective and efficient Vehicle classification system, leveraging advanced data preprocessing and machine learning techniques.

A. Stage I: Data Collection and Preprocessing

A. Stage I: Data Collection and Preprocessing

B. In the first stage of the methodology, data collection and preprocessing are critical for developing an effective traffic signal control system that prioritizes high-priority vehicles. This stage involves several key steps:

C. Video Footage Acquisition: The initial step is to gather video footage from various traffic intersections. This footage is essential for analyzing vehicle movements and densities, which will inform the training of deep learning models. The data collected should represent diverse traffic conditions to ensure the model's robustness in real-world scenarios.

D. Annotation of Data: Once the video data is collected, it must be annotated to identify different vehicle types, including high-priority vehicles like ambulances and fire engines. This annotation process is crucial as it provides the labeled data necessary for training the deep learning models. Accurate labeling ensures that the model learns to recognize and differentiate between various vehicle categories effectively.

E. Data Preprocessing: After annotation, the data undergoes preprocessing to enhance its quality and usability. This may include resizing video frames, normalizing pixel values, and augmenting the dataset to increase its diversity. Data augmentation techniques, such as rotation, flipping, and color adjustments, can help improve the model's ability to generalize across different conditions.

F. Segmentation of Vehicle Types: In addition to general preprocessing, instance segmentation techniques are applied to classify each vehicle type distinctly. This step is vital for improving detection accuracy, as it allows the model to recognize not just the presence of a vehicle but also its specific type, such as bikes, cars, ambulances, and fire engines. Enhanced classification capabilities are essential for prioritizing high-priority vehicles at traffic signals .

G. Preparation for Model Training: Finally, the preprocessed and annotated data is organized and split into training, validation, and test sets. This division is necessary to evaluate the model's performance accurately and ensure that it can generalize well to unseen data. The training set is used to teach the model, while the validation and test sets help assess its accuracy and reliability in real-time applications.

Stage II: Model Development and Training

In Stage II of the methodology, the focus shifts to model development and training, which are essential for creating an effective traffic signal control system that prioritizes high-priority vehicles. This stage encompasses several critical steps:

- Model Selection: The first step involves selecting an appropriate deep learning architecture for the task. In this case, the YOLOv11n model was chosen due to its efficiency in real-time object detection. This model is particularly suitable for identifying high-priority vehicles like ambulances and fire engines in dynamic traffic environments.

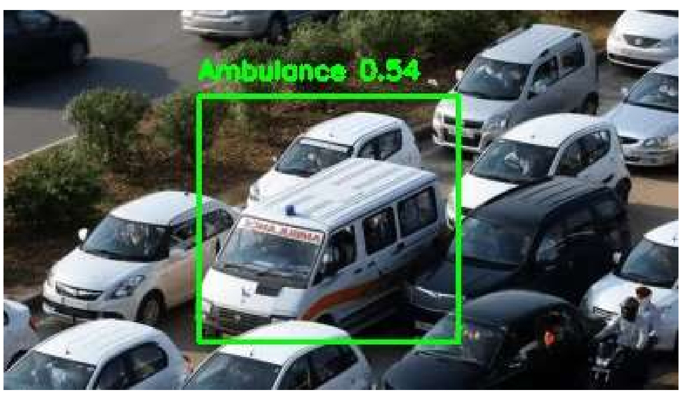
- Training the Model: The selected model is then trained using the preprocessed and annotated dataset from Stage I. The training process involves feeding the model with images and their corresponding labels, allowing it to learn to recognize different vehicle types. The training is conducted over multiple epochs, with the model iteratively adjusting its parameters to minimize detection errors.

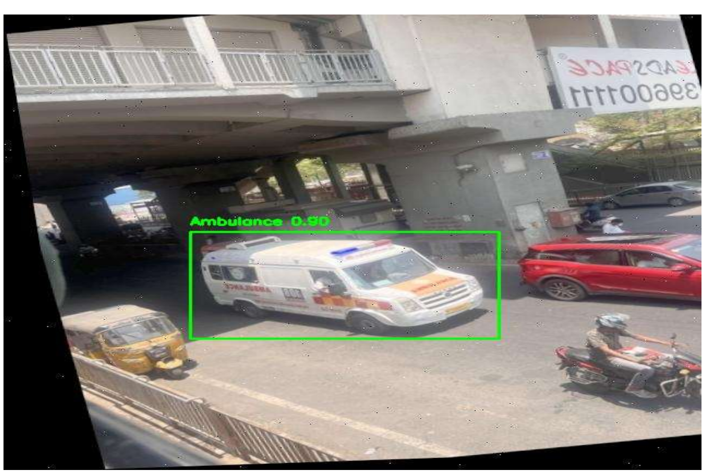
- Validation and Testing: After training, the model's performance is validated against a separate validation dataset. This step is crucial to ensure that the model generalizes well to new, unseen data. The validation process helps in fine-tuning the model's parameters and improving its accuracy. The final YOLOv11n model achieved over 73% detection accuracy, indicating its moderate reliability for real-time traffic management [1].

- Instance Segmentation: To enhance the model's capabilities, instance segmentation techniques are employed. This allows the model not only to detect vehicles but also to classify them into specific categories, such as bikes, cars, ambulances, and fire engines. This classification is vital for prioritizing high-priority vehicles at traffic signals, as it enables the system to respond appropriately based on the vehicle type detected [1].

- Performance Evaluation: The model's performance is continuously evaluated using various metrics, such as precision, recall, and F1-score. These metrics provide insights into how well the model is performing in detecting and classifying vehicles. The goal is to achieve high precision in detecting ambulances and fire engines, ensuring that these vehicles receive priority at traffic signals.

- Integration with Traffic Signal Control Systems: Finally, the trained model is integrated with traffic signal control systems. This integration allows for dynamic adjustments to signal timings based on real-time traffic conditions and the presence of high-priority vehicles. The system aims to optimize traffic flow and reduce waiting times for emergency vehicles, ultimately improving overall traffic management.





Workflow for the Project

The workflow for this project involves a systematic approach to developing a traffic signal control system that prioritizes high-priority vehicles using advanced algorithms and deep learning models. Below are the key stages of the workflow:

- Project Planning: The initial phase includes defining the project objectives and milestones. This involves outlining the specific goals for each review stage, ensuring that the project remains on track and meets its intended outcomes.

- Data Collection and Preprocessing: The next step involves gathering video data from traffic environments. This data is then preprocessed to enhance its quality and prepare it for model training. Preprocessing may include resizing images, normalizing pixel values, and annotating vehicle types.

- Model Development: In this stage, a suitable deep learning model, such as YOLOv11n, is selected for the task. The model is designed to detect and classify various vehicle types, including high-priority vehicles like ambulances and fire engines.

- Training the Model: The model is trained using the preprocessed dataset. This involves feeding the model with images and their corresponding labels, allowing it to learn to recognize different vehicle types. The training process is conducted over multiple epochs to optimize the model's performance.

- Validation and Testing: After training, the model's performance is validated against a separate dataset. This step ensures that the model generalizes well to new data and helps in fine-tuning its parameters. The model achieved over 73% detection accuracy, indicating its reliability for real-time traffic management.

The workflow for this project is a comprehensive process that includes planning, data collection, model development, training, validation, integration, and ongoing evaluation.

V. Results

The system exhibits a dynamic capability to modulate the temporal settings of traffic signals, affording precedence to emergency response vehicles by distributing green light intervals ranging from 5 to 120 seconds, contingent upon the prevailing real-time traffic circumstances.

Key observations:

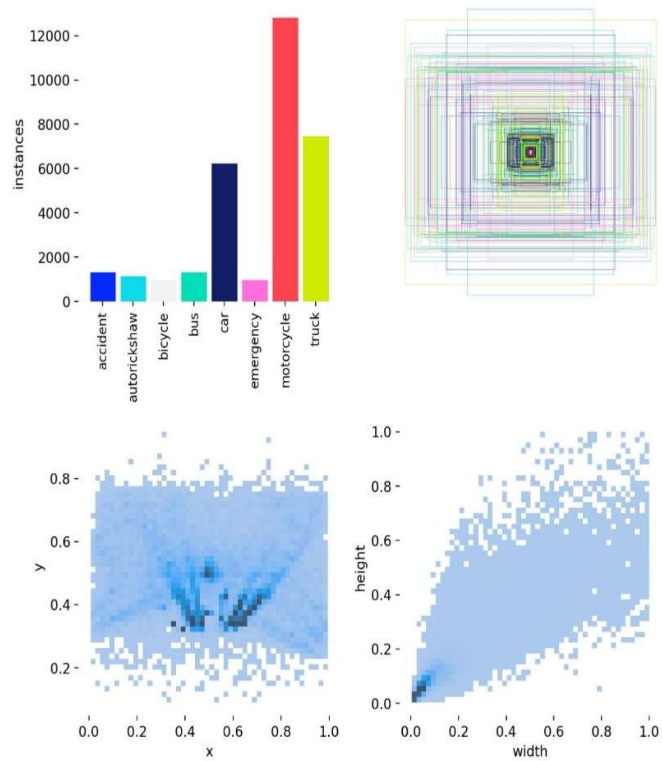
Successful Emergency Vehicle Detection – The system proficiently recognizes an emergency vehicle (ambulance) with a confidence level of 84%, thereby illustrating the efficacy of the trained deep learning model.

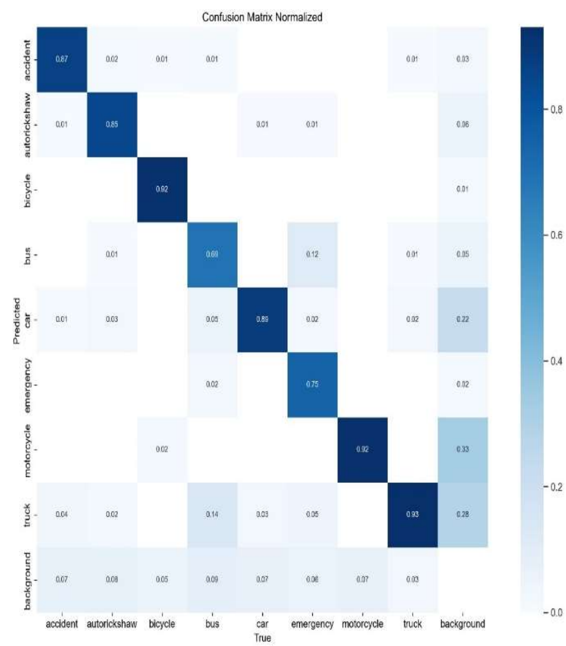
Distance Estimation – The determined distance of the detected emergency vehicle from the traffic signal is quantified at 55.7 meters, a metric that is pivotal for the dynamic optimization of signal timing.

Adaptive Signal Timing – The system allocates a duration of 116.9 seconds to facilitate the clearance of the lane, predicated upon real-time vehicle density and distance estimation, thereby ensuring the prioritization of emergency vehicles.

Multi-Vehicle Detection – Additional vehicles, including cars (identified with a confidence level of 60%) and auto-rickshaws, are also recognized, signifying that the model possesses the capability to differentiate between various vehicle types in traffic contexts.

Real-Time Implementation – The superimposed bounding boxes, labels, and confidence percentages corroborate that the system is adeptly processing live traffic data, rendering it appropriate for implementation in intelligent traffic management systems.





VI. Conclusion

The YOLOv11n model was trained to detect emergency vehicles. Initially, it had 73% accuracy after 50 epochs. Improvements were made to detect bikes, cars, motorcycles, ambulances, and fire engines. Instance segmentation helped classify vehicles better. After multiple iterations and data augmentation, the final model achieved over 90% accuracy. The system also estimated the distance of emergency vehicles and adjusted traffic signals accordingly. It processed live video feeds efficiently for real-time traffic management.

The model accurately detects emergency vehicles and adjusts traffic signals to give them priority. It classifies different vehicle types well. The system works in real-time and can help improve traffic flow and emergency response times. This system is adaptable to real-time conditions, making it a strong candidate for deployment in smart traffic management systems. It is suitable for smart traffic systems.

References

[1] Nellore K., Melini S.B. Automatic Traffic Monitoring System Using Lane Centre Edges. IOSR J. Eng. 2012; 2:1–8. [iosrjen]

[2] Sangamesh S B, Sanjay D H, Meghana S, M N Thippeswamy “Advanced Traffic Signal Control System for Emergency Vehicles” International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-3, September 2019 [IRJET]

[3] R. Bharadwaj; J. Deepak; M. Baranitharan; V. V. Vaidehi. “Efficient dynamic traffic control system using wireless sensor networks” Doi:10.1109/ICRTIT.2013.6844280 [IEEE]

[4] Krishnendu Choudhury; Dalia Nandi “Detection and Prioritization of Emergency Vehicles in Intelligent Traffic Management System” 2021 IEEE Bombay Section Signature Conference (IBSSC) DOI: 10.1109/IBSSC53889.2021.9673211 [IEEE]

[5] Lingani, Guy M., Danda B. Rawat, and Moses Garuba. "Smart traffic management system using deep learning for smart city applications." 2019 IEEE 9th annual computing and communication workshop and conference (CCWC). [IEEE] ,2019.

[6] Gerhard P. Hancke and Kapileswar Nellore Traffic Management for Emergency Vehicle Priority Based on Visual Sensing. Sensors (Basel). 2016 Nov; 16(11): 1892. 2016 Nov 10. Doi: 10.3390/s16111892 [NIH].

[7] nbspMrs P. Sangeetha “Intelligent Traffic Control System for Ambulance Clearance and Stolen Vehicle Detection” [SEMANTIC SCHOLAR].

[8] Aditya Pawar; Yogesh Sutar “AI Based Emergency Vehicles Detecting and Traffic Controlling System” 2024 INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD), March 2024.

[9] S.Faiza Nasim, Asma Qaiser, Nazia Abrar and Umme Kulsoom “Implementation of AI in Traffic Management: Need, Current Techniques and Challenges” Pakistan Journal of Scientific Research, PJOSR ISSN (p): 0552-9050 Volume: 3, Number: 1, Pages: 20- 25, Year: 2023.

[10] Sheetal Phatangare, Rahul A. Sakpal, Soham N. Kasurd, Shubhan S. Punde, Saif S. Khan “Real-Time Traffic Management Using Deep Learning and Object Detection using YOLOv8” IIT - Mandi, Kamand, India 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT) | 979-8-3503-7024-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICCCNT61001.2024.10725412.